Loan Growth and Risk:

Evidence from Microfinance Institutions in Africa

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Declaration

I declare that this thesis is my own work, except where acknowledged in the text. I further declare that this thesis has not been submitted for a degree at any other university.

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10th January 2019

Date

Abstract

Microfinance markets in Sub-Saharan Africa (SSA) have experienced remarkable growth, particularly after the early 2000s. Since microfinance institutions (MFIs) provide financial services such as loans, savings and insurance to poor clients who face exclusion from formal financial institutions, they are considered as one of the most prolific tools to alleviate poverty and achieve financial inclusion in developing countries. These institutions are of particular importance in SSA, given that the region has the highest poverty levels in the world and the highest levels of financial exclusion. However, in recent years the fast loan growth of MFIs has been accompanied increasingly by loan delinquencies which threaten the financial health of these institutions. This is a major concern for policymakers, regulators and practitioners given the developmental importance of microfinance in the region. Despite the pivotal role of microfinance, there is only a very limited number of studies that either investigate the underlying reasons for the fast growth of MFIs or that identify the determinants of credit risk in MFIs in this particular region of Africa.

Motivated by both the remarkable loan growth and the rising credit risk that MFIs experienced and the fact that SSA has been neglected in the relevant literature, this thesis provides evidence from the region on the factors that contribute to MFIs' growth, the determinants of MFIs' credit risk as well as the factors that influence access to MFIs credit. The latter pays particular attention to the effect of mobile financial services (MFS) on borrowing from MFIs, an aspect that has been ignored in previous scholarly work. Furthermore, the thesis overcomes the limitations of previous studies that employed static regressions, which are limited in dealing with panel endogeneity bias, by focusing on the dynamic aspects of loan growth and credit risk.

The thesis is structured around three related studies that are presented in three chapters, namely Chapter 2, Chapter 3 and Chapter 4. The purpose of the second chapter is to identify the factors

that explain variations in loan growth in the region's MFIs. This is an important issue as high loan growth may pose significant stability risks in the microfinance sector via a deterioration in portfolio quality. The chapter applies two-step system generalised method of moments estimators on data for 34 countries in SSA over the period 2004 - 2014. The results show that loan growth is higher in MFIs that have lower risk exposure, higher capital asset ratios and already recording high growth. Similarly, loan growth is higher in countries with better economic prospects, and in those with sound private sector policies and regulations. Against expectations, loan growth is faster in countries with poor legal rights of borrowers and lenders.

Credit risk in microfinance institutions in SSA has been rising, and the financial health of these institutions remains an issue of concern. Hence, Chapter 3 examines the factors that explain variations in credit risk in MFIs in the region. Similarly, the chapter employs a system GMM approach on data for 34 countries in SSA over the period 2004 – 2014. Results suggest that the main predictors of credit risk in SSA are lagged credit risk, loan growth, provisions for loan impairment, GDP per capita growth and ease of getting credit. In addition, the study identifies threshold effects in the relationship between credit risk and loan growth. Credit risk falls with loan growth until a trough at 36.8% when this relationship is reversed. On the regional scale, comparisons suggest that credit risk is most persistent in East Asia and the Pacific but least persistent in SSA.

Relatively few scholarly works have analysed the influence of mobile financial services (MFS) on access to credit. Chapter 4 aims to identify the factors that explain the differences in the propensity to use loans from MFIs in Kenya, paying particular attention to the effects of mobile money (M-money), mobile banking (M-banking) and mobile credit (M-credit). Kenya is an interesting case study because the country outperforms other SSA countries in terms of financial and digital inclusion. The study applies a probit model using FinAccess cross sectional data that was collected in 2013 (N=6112) and 2015 (N=8665). After addressing endogeneity concerns in the data, the 2013 results suggest that the factors that make a significant difference in the likelihood of using MFI credit include income, gender and type of cluster. An important observation is that non-poor users of M-money are more likely to use microcredit. The 2015 results show that the likelihood of using MFI credit is lower among those using M-banking and M-credit as well as among males and married persons. However, higher income, being educated, higher household size and being located in a rural cluster are associated with a higher propensity to use MFI credit. In addition, the results suggest a U-shaped relationship between age and the probability to use MFI credit. Similarly, the negative relationship between the likelihood of using MFI credit and using M-banking and M-credit suggests that the introduction of MFS in the financial sector has resulted in the migration of clients from microfinance products towards mobile-based financial services.

In terms of policy, two recommendations stand out. Firstly, since dynamics matter for both loan growth and credit risk, credit management strategies that incorporate past risk and loan performance are likely to be more effective. Secondly, the evident trade-offs between loan growth and credit risk confirm the fact that modest loan growth is not the source of instability within the region's microfinance sector. However, the presence of threshold effects suggests that MFIs should determine the turning points for lending growth because excessive growth in loans can be perilous to the existence of the institution itself, and the sector by extension.

Dedication

To my parents Lincoln Dobi and Truphena Andeyo.

Acknowledgements

As the adage goes, every long journey begins with one step. My PhD journey, which started in January 2014 was not an entirely pleasant experience. The five-year period of coursework and research was not a piece of cake. It started with all odds against my successful completion of the PhD. The first two years turned out to be the toughest. Three staggering blows filled this journey with pain. I had to spent time shuffling between nursing a sick wife and a gruelling coursework whilst I was not on salary. I lost my wife in 2015 and everything seemed to fall apart. I was left devastated and heartbroken. Though this was a season of tears, sorrow and pain, it was also the season that gave me the opportunity to become more human, humble and strong. As the psalmist writes in Chapter 124 verses 1 and 3 "If it had not been the Lord who was on our side, now may Israel say; If it had not been the Lord who was on our side, when men rose up against us: Then they would have swallowed us up quick, when their wrath was kindled against us". By His grace, God kept me strong. By His righteous right hand, he gave me comfort and through His Word He sharpened my focus.

This thesis is a product of the labours of many people as well as the resources of many organisations. I will never forget the labours of my supervisor, my kindred and my friends. I will ever be grateful to my employer, KIPPRA, the Government of Kenya, African Economic Research Consortium (AERC) and United Nations University World Institute of Development Economics Research (UNU-WIDER).

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During this PhD journey, I applied for a United Nations University World Institute for Development Economics Research (UNU-WIDER) PhD fellowship in 2016. I was awarded the fellowship, which funded my 3 months (April to June 2017) sojourn at the UNU-WIDER headquarters in Helsinki, Finland. During my stay at UNU-WIDER, the technical reviews with my fellow interns and research fellows enriched chapter 3 of my thesis particularly through the comments I received during the internal seminar held at the Institute as well as the technical input of my mentor, Dr Kyle McNabb.

List of abbreviations

AMFI	Association of Microfinance Institutions
ASCA	Accumulating Savings and Credit Association
AR	Auto Regressive
CEMAC	Economic and Monetary Community of Central Africa
CPI	Consumer Price Index
EAP	Eastern Asia and the Pacific
EECA	Eastern Europe and Central Asia
FDI	Foreign Direct Investment
FI	Financial Intermediary
GDP	Gross Domestic Product
GMM	Generalised Method of Moments
GNI	Gross National Income
HHI	Herfindahl -Hirschman Index
IV	Instrumental Variable
LAC	Latin America and the Caribbean
M3	Broad money supply
MFS	Mobile Financial Services
MFI	Microfinance Institution
MENA	Middle East and North Africa
MIX	Microfinance Information eXchange
M-Banking	Mobile Banking
M-Credit	Mobile Credit
M-PESA	Mobile Money
NASSEP	National Sample Survey and Evaluation Programme
NGO	Non-Government Organisation

NPV	Net Present Value
OLS	Ordinary Least Squares
SA	South Asia
SACCO	Savings and Credit Cooperative Associations
SME	Small and Medium Enterprise
SSA	Sub-Saharan Africa
TGA	Temporary Government Administration
TSLS	Two Stage Least Squares
USAID	United States Agency for International Development
USD	United States Dollar
WAEMU	West African Economic Monetary Union
WDI	World Development Indicators

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Chapter 1

Introduction

1.1 Introduction

Broadly, the concept of microfinance encompasses the provision of credit plus the accumulation of savings and other financial services, including the supply of insurance policies, in lesser amounts to cater for poor clients, who are conventionally believed to lack the capacity to access the formal financial institutions (Dichter, 2007; Onyuma and Shem, 2005). Since microfinance targets the "bottom of the pyramid", it has been viewed as one of the most prolific tools for alleviating poverty and achieving financial inclusion in developing countries (Triki and Faye, 2013). This is because microfinance offers not only financial services but also add-ons that develop sectors such as education, nutrition, health and also build entrepreneurial skills.

Microfinance markets in Sub-Saharan Africa (SSA) have witnessed remarkable growth, particularly after the 2000s. Their gross loan portfolio grew by about 23 times between 2000 and 2014, which represents an annual median growth rate of 25% per annum (see Appendix Table A1). During the same period, the number of active borrowers expanded by about 5 times representing an annual median growth rate of 18%. Assets of the sector have mushroomed by a factor of 27 while the number of depositors grew from 773,000 in 2000 to 14.8 million in 2014, representing an annual median growth of 22.7%.

Between 2000 and 2007, median annual growth in gross loan portfolio and assets in SSA was 36.8% and 38.2%, respectively. Over this period, the number of borrowers and depositors grew annually by 24% and 25.2% respectively. Although these growth patterns slowed down in the

2008-2014 period, partly due to the adverse effects of the global financial crisis (Wagner and Winkler, 2013), there have been concerns among development practitioners and regulators (Shankar and Asher, 2010) regarding this rapid expansion in microfinance markets. Sceptics wonder whether this rapid growth is truly beneficial (Wichterich, 2012) and whether this growth is too fast (Gonzalez, 2010). Moreover, there are fears that such growth may not be sustainable in the medium term and may pose significant risks to the stability of the financial sector via a deterioration in portfolio quality (or an increase in non-performing loans). This last concern is consistent with real business cycle theory which associates episodes of credit booms with overheating of financial markets, which eventually end up as financial crises (Elekdag and Wu, 2011).

Fears that fast loan growth in microfinance markets could be harmful to the stability of the sector have arisen from episodes of increasing loan default rates. Credit risk is usually reflected as an increase in non-performing loans and indicates the increasing vulnerability of a financial institution (Craig and Dan, 2013). In 2000, credit risk was 3.5% in SSA microfinance institutions (MFIs), which increased to 8.2% in 2010 and 8.1% in 2014 (see Appendix Figure A2 Panel A). Similarly, there have been episodes of ailing and dying MFIs in India, Morroco, Pakistan, Nicaragua, Bosnia and Herzegovina (Chen et al., 2010; Wichterich, 2012). In SSA, there have been insolvencies in Ghana (50 MFIs in 2013 alone), the West African Economic Monetary Union (25 MFIs), the Economic and Monetary Community of Central Africa (4 MFIs) and one each recorded in Zambia and South Africa (Boateng et al., 2016; Riquet and Poursat, 2013). This instability in the microfinance sector has been attributed to the failure of MFIs to prioritize risk management and to other factors such as weak regulation, excessive market growth, predatory lending, fraud and loss of focus (Lutzenkirchen et al., 2012; Marulanda et al., 2010). Despite these episodes, there has been little empirical analysis to unravel the relationship between loan growth and portfolio at risk in SSA microfinance markets. Furthermore, little is known on how such growth, especially when it is excessive, impacts asset quality in microfinance. The aim of this thesis is to provide new evidence on the trade-offs between loan growth and credit risk in MFIs located in SSA and to analyse the causes of loan growth and the associated risk. It also explores demand-side factors that could be used to explain the expansion witnessed in the region's microfinance markets.

At the global level, scholarly works have attempted to explain variations in loan growth in microfinance markets (Wagner and Winkler, 2013; Ahlin et al., 2011). Whereas Wagner and Winkler (2013) sought to explain whether microfinance was exposed to global financial crises, Ahlin et al. (2011) were more concerned with the effect of macroeconomic and institutional factors on the microfinance sector. Regarding credit risk exposure, empirics have been concerned with the roles of gender (Schmit and Marrez, 2010; D'espallier et al., 2011), group lending (Crabb and Keller, 2006), macroeconomic shocks (Gonzalez, 2007), loan growth (Gonzalez, 2010) and loan size (Chikalipah, 2018). In addition, Sainz-Fernandez et al. (2015), Yimga (2016), Lassoued (2017) and Noomen and Abbes (2018) sought to identify the drivers of credit risk. From the demand side, studies that have sought to explain why access to finance differs across households and countries include Mohieldin and Wright (2000), Okurut (2006), Manrique and Ojah (2004), Zeller (1994), Okurut et al. (2005), Khoi et al. (2013) and Farazi (2014). Generally, these studies have identified individual factors, household characteristics, financial factors, sector-level attributes and macro-institutional factors as the key determinants of access to credit.

A review of the relevant literature reveals glaring gaps in studies that analyse the determinants of both loan growth and risk in microfinance markets first of which is that SSA has been neglected in the relevant literature. Secondly, previous studies have paid little attention to the dynamic aspects of loan growth and risk. They employed static regressions, applying either random effects and fixed effects estimators which are limited in dealing with panel endogeneity bias. They also failed to deal with endogeneity issues that arise from omitted variables, measurement errors and reverse causality. The third gap observed is that very few studies have explored these issues at the disaggregated level, yet such analysis unmasks important differences in the effects of region-specific idiosyncratic factors. Undertaking international comparisons is useful because it allows one to test whether factors that turn out statistically significant in SSA are also important elsewhere. Finally, relatively few scholarly works have analysed the effect of mobile financial services (MFS) on access to credit. Given these knowledge gaps, this thesis approaches microfinance from both the demand and supply sides. From the supply side, the thesis considers the lending behaviour in MFIs and examines whether excessive lending is associated with higher risk exposure and whether any non-linearities exist in this relationship. The demand side looks at some of the potential barriers to accessing MFI credit at the household level.

Specifically, the aim of Chapters 2 and 3 is to identify the factors that determine loan growth and assess predictors of credit risk differences in SSA, respectively. Both chapters also compare and contrast the statistical significance of these factors in other global regions. Chapters 2 and 3 apply system generalised method of moments (GMM) on data from 2004-2014 to investigate the determinants of loan growth and credit risk in SSA microfinance markets while also identifying any trade-offs that may exist between both variables. Data was derived from four sources: MIX dataset, World Development Indicators, World Governance Indicators and Doing Business Indicators. These two chapters contribute to the literature in several ways. Firstly, they provide evidence on SSA, which is a region that has been neglected in the literature. Secondly, they extend the models that have been used previously by introducing dynamics as well as specific and idiosyncratic factors of the SSA region. Thirdly, they use system GMM estimators, which have been known to accommodate endogeneity biases. Lastly, they identify predictors of loan growth and risk in Eastern Asia and the Pacific (EAP), Eastern Europe and Central Asia (EECA), Latin America and the Caribbean (LAC) and South Asia (SA).

Both Chapters establish the existence of trade-offs between loan growth and risk. Loan growth was higher in MFIs facing lower risk exposure and vice versa. In contrast to Chapter 2, the third Chapter establishes non-linearities between loan growth and credit risk, thus providing evidence of threshold effects. The two Chapters also report that dynamics are important in predicting both loan growth and credit risk, which points to the persistence of these two variables. In addition, the analysis in Chapter 2 shows that loan growth in MFIs for the entire period (2004-2014) is higher when ease of getting credit is lower and when capitalisation, GDP growth and regulatory quality are higher. According to Chapter 3, other predictors of credit risk in SSA MFIs are provisions for loan impairment, GDP per capita growth and ease of getting credit. A comparative analysis of credit risk determinants in Chapter 3 shows that credit risk was persistent in all regions (ECA, EECA, LAC and SA). The same analysis in Chapter 2 identifies loan growth as an important predictor of credit risk in all regions. A global analysis of loan growth determinants in Chapter 2 also shows that loan growth is persistent in all regions.

Chapter 4 examines the differences in the propensity to use microcredit in Kenya using FinAccess survey data collected in 2013 and 2015, paying particular attention to the effects of MFS including M-banking, M-money and M-credit on the likelihood of using microcredit. Kenya is an interesting case study because the country out-performs other countries in the region in terms of both financial and digital inclusion. The 2014 Global Financial Inclusion database shows that out of 38 SSA countries, account ownership in Kenya was 74.7%

compared to 34.2% for SSA while mobile money account penetration in Kenya was 58.4% against 11.5% for SSA. A 2016 report by the Brookings Institution comparing 26 countries in terms of M-money adoption ranked Kenya on top of the sample countries[1]. The high rating of the country has been attributed to the financial innovation of M-PESA[2], which has drastically altered the way people save, borrow and transact. Significantly lowering many barriers that discourage poor people from accessing banking services, M-PESA has also had an impact on access to microcredit following its explosion in the last few years. After addressing endogeneity concerns via instrumental variables (IV 2SLS and IV Probit), the results in Chapter 4 show that the probability of using MFI credit is lower among those using M-banking and M-credit as well as among males and married persons. However, higher income, education level, household size and being located in a rural cluster is associated with a higher probability to use MFI credit. Furthermore, the analysis shows evidence of a U-shaped relationship between the probability of using MFI credit and age.

The findings in this thesis have important policy implications for both practitioners and regulators of microfinance in SSA. The finding that loan growth and credit risk are negatively correlated implies that modest loan growth is not a source of instability in the MFI sector. Rather, excessive loan growth is potentially harmful to the instability of MFIs. Therefore, these institutions should be encouraged to identify the threshold at which loan growth becomes harmful to their stability. Another pivotal finding is that dynamics predict lending growth and credit risk. This implies that lending methodologies, such as credit scoring and credit modelling, that incorporate past lending and loan defaults are likely to be more effective.

[1] Refer to Villasenor et al. (2016)

[2] Introduced into the Kenyan market in 2007 by Safaricom, M-PESA consists of two words. "M" stands for "mobile" and "PESA" is a Kiswahili word that means "Money". Put together, "M-PESA" means "Mobile Money" which is a mobile phone platform that allows users to exchange cash for an "e-float" on their phones, to send e-float to other cellular phone users and to exchange e-float back to cash (Mbiti and Weil, 2011).

Regarding the negative correlation between the use of microcredit, on one hand, and the use of M-banking and M-credit, on the other hand, the results imply that the introduction of MFS has heightened competition in the traditional microfinance sector. Hence, MFS should be designed in ways that do not harm access to microcredit.

1.2 Why Focus on Sub-Saharan Africa?

There are two main reasons why this thesis is centred on this particular region of Africa. Firstly, SSA has the highest poverty levels in the world and the highest levels of financial exclusion (Begle et al., 2016; World Development Indicators, 2017). Secondly, indicators of performance show a significant difference between SSA and non-SSA MFIs (See Appendix Table A2). At the global level, SSA has both high poverty and low financial deepening. About 43% of the population in SSA lives on less than USD 1.90 a day compared to 11% in developing countries (Begle et al., 2016). Between 2004 and 2014, the share of domestic credit to the private sector by banks in GDP was 17% for SSA and 34% for developing countries[3]. These statistics suggest a bigger role for microfinance to promote financial inclusion and poverty reduction in SSA than elsewhere. In spite of this evidence, SSA remains the least researched area in terms of microfinance; studies seeking to understand the implications of the fast growth in microfinance markets and the associated risks are few.

Furthermore, this thesis focuses on SSA because the indicators in Appendix Table A2 provide several reasons to believe that there is a significant difference in the performance of MFIs in SSA as compared to their counterparts in other developing regions. Using several MFI performance indicators, the t-test for equality of means confirms this conjecture. These

[3] Author's computation using World Development Indicators (https://elibrary.worldbank.org/doi/pdf/10.1596/978-0-8213-7386-6)

indicators include institutional characteristics, outreach, sustainability, revenue mobilization, spending levels, efficiency, productivity and risk exposure. On the basis of outreach, SSA lags behind in terms of number of active borrowers, gross loan portfolio and the share of women in the total number of active borrowers. There is a difference in gross loan portfolio of USD 12.4 million between an average MFI in SSA and an MFI elsewhere. This difference is significant at 1%. In terms of overall financial performance, MFIs in SSA are generally less operationally self-sustainable than MFIs elsewhere. Two indicators on revenues, namely financial revenue ratio and yield on gross portfolio, confirm that average loan interest rates charged by MFIs are relatively higher in SSA MFIs compared to rates charged on loans in other developing regions. The analysis also shows that MFIs in SSA are relatively inefficient and less productive on the basis of the following ratios: operating expense ratio, personnel expense ratio, borrowers per staff member and depositors per staff member. A comparison between the two groups in terms of loan write-offs and non-earning liquid assets as percentage of total assets shows that MFIs in SSA are not only more liquid but they are also riskier compared to their counterparts in other regions.

1.3 Structure of the Thesis

The rest of the thesis is presented as follows. Chapter 2 identifies the factors that explain variations in loan growth in SSA MFIs while Chapter 3 examines their exposure to credit risk. The next chapter explores the impact of mobile-based financial services on microfinance and explains why access to MFI credit differs among households in Kenya. Concluding the thesis, Chapter 5 provides some policy recommendations, limitations and suggestions for further research in the microcredit sector.

Chapter 2

Determinants of Loan Growth in Microfinance Institutions: The Case of Sub-Saharan Africa and Comparisons with other Regions of the World

2.1 Introduction

Between 2000 and 2014, lending in microfinance markets in Sub-Saharan Africa (SSA) rose sharply. The number of borrowers increased from 854,692 in 2000 to about 4.3 million in 2014. Gross loan portfolio, which stood at US$250 million in 2000 rose to about US$5.9 billion in 2014. The stock of microfinance assets rose from US$360 million in 2000 to US$9.9 billion in 2014. Between 2000 and 2008, credit expanded at about 36.8% annually and the cross-MFI variability in the loan growth was also high (Appendix Figure A1). However, there was a decline in both the loan growth rate and variability during the 2009-2014 period implying that outreach gains that were experienced before 2009 were beginning to level out. High variability during the 2004-2008 period meant that the sharp rise in lending was far from uniform across MFIs.

Mean loan growth in SSA was 28% between 2004 and 2014 (Appendix Table A4). In financial markets, this is considered rather high. But the percentage masks huge cross-country and cross-MFI disparities. For individual countries, loan growth ranged from 87.3% in Guinea-Bissau to 11.1% in Central African Republic and Niger, although some countries such as Comoros and Zimbabwe witnessed negative loan growth rates. At the MFI level[4], the fastest loan growth rates of 530% and 440% were recorded by Reliance (located in Gambia) and Abidjan Credit

[4] This data is not reflected in Appendix Table A4 but is available from the author upon request.

(located in Ivory Coast), respectively. The lowest loan growth rates of -440% and -390% were recorded by CANARI (located in Ivory Coast) and Faching (located in Zimbabwe), respectively.

From a policy perspective, sceptics are wondering whether this growth in microcredit markets is too fast (Gonzalez, 2010). In fact, it has been feared that such loan growth rates may pose significant stability risks in the MFI sector via a deterioration in portfolio quality (Yimga, 2016; Chen et al., 2010; Lutzenkirchen and Weistroffer, 2012). These concerns are consistent with real business cycle theory which associates credit booms with growing financial crises (Elekdag and Wu, 2011). In fact, evidence indicates that many bank crises were preceded by rapid credit growth including the recent global recession of 2007-2009 (Amri et al., 2012). Therefore, policies to promote the growth of MFIs in SSA need to be based on a good understanding of the drivers of loan growth.

Whereas the above disparities and concerns have been evident for some time, extant evidence at the global level on what explains the variations in the loan growth rate in microfinance markets is now emerging, though knowledge is still limited and inconclusive. For example, studies have begun to question whether microfinance (which was initially cushioned from systemic shocks) has become vulnerable to such shocks as is the case in the banking sector (Wagner and Winkler, 2013). Evidence seems to be in the affirmative. There is also focus on whether the macro-institutional environment affects the performance of MFIs (Ahlin et al., 2011)[5]. Again, evidence seems to be in the affirmative. But these studies have paid little attention to dynamic aspects of loan growth and therefore use static regressions applying either

[5] The main question was whether the macro-institutional environment influences the success of microfinance using various measures including operational self-sustainability, interest mark-up, loan loss expense rate, risk, cost per dollar loaned, cost per borrower, MFI growth, loan growth, loan size growth and borrower growth.

random effects and fixed effects estimators which are limited in dealing with panel endogeneity bias. They fail to address endogeneity issues that arise from omitted variables, measurement errors and reverse causality. Although mean tests confirm that MFIs in SSA are different from their counterparts elsewhere, there is not yet evidence on factors that determine loan growth in SSA[6]. In addition, very few studies have explored the issue at the disaggregate level yet such an analysis unmasks important differences in the effects of regional-specific idiosyncratic factors. Undertaking international comparisons is useful because it allows one to test whether factors that turn out statistically significant in SSA are also important elsewhere. Given these knowledge gaps, this paper aims to identify the factors that determine loan growth differences in SSA and distinguish the various ways such factors affect loan growth in other geographical regions.

This chapter contributes to microfinance literature in two ways. Firstly, it extends knowledge in this area by providing evidence from SSA, a region that has been neglected in the relevant literature despite the important role that MFIs role in the region. Secondly, it expands the models that have been employed in the past by considering the dynamic aspects of microfinance as well as the specific and idiosyncratic factors of the SSA region. The chapter applies panel generalised method of moments (GMM) estimators, which are versatile in dealing with endogeneity biases that are pervasive in socio-economic data.

Empirical findings reveal that micro-level, macroeconomic and institutional factors are significant predictors of loan growth in SSA. Four main findings stand out. First: loan growth is faster among MFIs that were already having high loan growth, which reflects persistence in

[6] Mean tests in Table 1 also reveal that the macro-institutional environment in SSA is significantly different from the levels existing in non-SSA countries.

loan growth. Second: loan growth is higher in MFIs facing lower risk exposure, that are well capitalised and those that are located in countries with high GDP growth rates and sound private sector policies and regulations. The third notable finding, contrary to expectations, is that loan growth is faster in countries with poor legal rights of borrowers and lenders. Finally, variables that are statistically significant in the SSA regressions do not necessarily remain significant in the regressions for the other regions (Eastern Asia and the Pacific, Eastern Europe and Central Asia, Latin America and the Caribbean and South Asia).

The next section of this chapter reviews the relevant literature and identifies some knowledge gaps. Section 2.3 presents the empirical model and discusses the data while Section 2.4 reports the results. Section 2.5 concludes the discussion and draws some policy implications.

2.2 Literature Review

2.2.1 Theoretical Literature

The economic theory suggests that the amount of credit extended by a financial institution is mainly determined by the business cycle (Bernanke et al., 1994), information (Stiglitz and Weiss, 1981), institutions (North, 1990) and monetary policy stance (Mishkin, 2013). The business cycle view is based on the interconnectedness of credit markets and the macroeconomy (Plosser, 1989). In these markets, optimizing decisions of lenders and borrowers interact to generate economy-wide cyclical patterns. An offshoot of this reasoning is the financial accelerator theory, which was pioneered by Bernanke et al. (1994). This theory explains how small adverse changes to the net worth of firms are amplified to propagate huge adverse financial and macroeconomic shocks, which in turn set in motion credit cycles. When the net worth of firms falls in the presence of financial frictions, agency costs of lending to such firms rise (Mishkin, 2013). Lenders become suspicious of such firms and are less willing to grant them credit because a decline in the firms' net worth gives them a higher incentive to invest in risky investment projects arising from the fact that they stand to lose less if the project fails. The firms respond by downscaling their investment plans which lowers economic activity. This has adverse knock-on effects on asset prices and the net worth of firms, perpetuating recurring cycles and feedback loops.

Business cycle theory predicts procyclicality between loan growth and economic upswings (Clair, 1992; Keeton, 1999; Quagliariello, 2007). In addition, it predicts countercyclicality between credit risk and economic upswings. When lending is excessive during an economic upswing, it ends up as a "credit crunch" during subsequent downturns (Berger and Udell, 2004). An economic boom is associated with higher profits, higher asset values and optimistic customer expectations (Quagliariello, 2007). Because aggregate demand will also be higher during an economic boom, demand for loans goes up because the loan servicing capacity of borrowers is enhanced. Banks take in more risk by giving new loans at lower interest rates and relaxed credit standards resulting in higher indebtedness among borrowers. There is a reversal of events during an economic downturn because loan performance problems appear – loan defaults will rise and growth in loans will be low. As such, phases of high loan losses tend to be preceded by phases of high loan growth. Similarly, macroeconomic variables may follow either a pro-cyclical or counter-cyclical pattern in the presence of economic upwings. For example, aggregate demand and inflation tend to be procyclical while unemployment and interest rates tend to be counter-cyclical.

Credit cycles are usually characterised by accelerated lending during business cycle expansions, with sharp reversals in lending during subsequent downturns. Keeton (1999) argues that the reversals do not always hold. Faster loan growth may not be followed with higher loan losses if there exist either demand or productivity shifts. An increased demand for credit unrelated to borrower's underlying creditworthiness will tend to boost loan growth and raise credit standards, reducing the likelihood of future loan losses. A productivity shock that could result from improved technology or lower oil prices has the effect of increasing the chances that a borrower of given characteristics can repay the loan, allowing banks to relax their collateral requirements or accept borrowers with poorer credit histories.

The second view identifies information as a key determinant of the lending decision because the parties contracting are imperfectly informed about each other (Stiglitz and Weiss, 1981). Before making the decision to lend, the creditor needs information about the borrower's risk attitude, goals and credit history; the viability of borrowers' projects as well as the borrower's other lenders (Djakov et al., 2007). When these are not satisfied, the creditor remains exposed to agency costs arising from adverse selection and moral hazard (Stiglitz and Weiss, 1981). With the prospect of uncertainty and the likelihood of loan default, the lender tends to incur extra costs to monitor the loans, screen the loan applicants and obtain sufficient collateral as an incentive to repay the loan. The higher the agency costs, the higher the probability of loan default, which reduces the willingness of the lender to extend new loans and renew old loans. Information asymmetry problem is usually more acute among SMEs who are the main clients to MFIs. These enterprises (SMEs) tend to be informationally opaque – they do not have a culture of maintaining up-to-date records and developing business plans (De la Torre et al., 2010).

The third determinant of lending by MFIs has been termed "the power of creditors" (Djakov et al., 2007). It is based on the idea that creditors are more willing to lend if they can easily enforce the loan contract. Contract enforcement guarantees property rights, lowers transaction costs and reduces opportunistic behaviour in lending (McMullen et al., 2008; North, 1990). A case in point is the finding that the prevalence of corruption resulted in taxing the operations of micro-enterprises, consequently constraining their expansion, reducing their demand for loans as well as the quality of microloans (Ahlin et al., 2011). Good institutions may also constrain lending by financial institutions. When a large proportion of the MFI loan portfolio is held by informal sector operators, a shrinking informal sector (caused by strengthening institutions) will imply lower loan demand. Udry (1990) finds that MFI loans by informal sector players are used for risk pooling. Therefore, the expectation is a negative relationship between stronger institutions and growth in lending.

The last view is the government's monetary policy stance. As explained by Mishkin (2013) and Hofmann (2004), there are several channels through which monetary policy is transmitted. Only four channels are highlighted here: traditional interest rate, bank lending, balance sheet and cash flow. According to the traditional Keynesian view, a contractionary monetary policy is associated with higher interest rate, which increases the cost of credit and lowers supply of loans. In the bank lending channel, the quantity of bank loans will fall in response to a contractionary monetary policy which lowers bank reserves and bank deposits. The balance sheet channel works via a fall in adverse selection and moral hazard which accompany a fall in the net worth of firms as a result of falling stock prices. Stock prices fall in response to a contractionary monetary policy. The cash flow channel also works through firm's balance sheet. Contractionary monetary policy has the effect of lowering firms' cash flow, which worsens the firms' balance sheet. When the balance worsens, the liquidity of the firm falls – curtailing its capacity to pay bills. When the firm's creditworthiness deteriorates, the lemons problem sets in resulting in a lower supply of loans.

2.2.2 Empirical Literature

The empirical literature on the determinants of credit growth in microfinance is scarce. During the financial crises of the 1980's and 1990s[7], microfinance exhibited two interesting features that later became the focus of research. The first one was the observation that MFIs emerged unscathed after the crises, even though the banking sector faced a lot of distress (Wagner and Winkler, 2013). It was puzzling that despite the fact that financial crises affected the banking sector (crisis prone), microfinance remained unaffected and "crisis free'. The second is the fact that accumulation of non-performing assets in MFIs did not result in loan write-offs because non-performing assets were always settled (Gonzales, 2010). These two features were attributed to high levels of discipline in lending, more productive use of loans by MSEs and insulation of MFIs from the global financial system (Wagner and Winkler, 2013).

The question of whether microfinance was significantly correlated to developments in international financial markets remained empirically untested until the study by Krauss and Walter (2009). The study used 1998-2006 cross country data to conclude that MFI growth and global market indicators were independent. This finding can be contrasted against Wagner and Winkler (2013) who found a significant and negative relationship between MFI real credit growth and the global financial crisis - the results being sustained even when the data is analysed by legal status of the MFI (except credit unions where the effect was insignificant) and regions (except South Asia). These findings are interpreted as evidence of exposure of microcredit to boom-bust cycles that characterise the traditional banking sector, thus pointing to the idea that rapid increases in lending by MFIs should be viewed as an indicator of either financial inclusion or financial distress. Ahlin et al. (2011) address the question: Does MFI

[7] During the 1980s, banking crises were experienced in the United Sates, Argentina, Chile, Czech Republic and Norway and during the 1990s in Indonesia, Thailand, South Korea, Malaysia, Venezuela, Mexico, Japan, Finland, Hungary, Brazil, Russia and Sweden (Mishkin, 2013)

success depend on the macro-institutional environment? Among other dependent variables, they considered extensive loan growth (number of borrowers) and intensive growth (average loan size). They find that the significant predictors of borrower growth include labor force participation, manufacturing value added and age of MFI. Predictors of loan-size growth were labor force participation, manufacturing value added and real GDP per capita. It is concluded that microeconomic factors as well as the macro-institutional environment do influence microfinance loan growth.

Whereas Krauss and Walter (2009) and Wagner and Winkler (2013) focused on the correlations between financial crises and microfinance, Gonzales (2010) was more concerned with thresholds in loan growth – by seeking to determine how much growth would be considered too much. Using quadratic relationships, the study identifies the turning points along the credit curves and provides evidence to suggest that the growth of loans in microfinance was not very high during the 2003 – 2008 period. This was implicitly taken to mean that the rapid growth in microfinance markets was more of a "catch-up effect" (movement towards an equilibrium) rather than a shift towards disequilibrium.

Some of the significant predictors of loan growth at the MFI-level as identified by Wagner and Winkler (2014) and Ahlin et al. (2011) include funding growth, credit risk, GDP growth, inflation, global financial crisis, current account balance, remittances, competition, size, political stability, corruption, labour force, age and manufacturing value added. Despite this evidence, there is yet no consensus as to which factors are most relevant in explaining credit expansion. The statistical significance of individual factors, as well as their signs and magnitudes vary across studies, thus, producing conflicting results. Moreover, an understanding of the drivers of credit growth in microfinance institutions is just an emerging area of research while the effect of some of these significant factors in SSA remains unknown.

Unlike MFIs, banks have been extensively researched partly because financial systems in many countries are bank-based (Mishkin, 2013) and partly because they face more exposure to international financial crises. In fact, early analyses of the rapid growth in credit were done in response to the credit market cycles of booms and busts in developed countries during the late 1980's and early 1990's (Hofmann, 2001). Such studies examined bank credit booms and their drivers[8] as well as the procyclicality of bank performance and the business cycle[9]. Credit booms have been defined as episodes of rapid credit growth (Dell'Ariccia et al., 2012) especially when the annual growth rate of the bank credit to the private sector as a share of GDP exceeds 20 per cent (Barajas et al., 2007). With credit booms defined in this way, it was shown that not all of them were bad – there were "bad booms" and "good booms". Good booms were associated with economies movement towards the equilibrium, defined as a "catch-up effect", but bad credit booms always fuelled economic crises.

In order to test the hypothesis that credit growth was procyclical, the approach has been to regress credit to private sector as a share of GDP against an economic activity variable (such as GDP growth, GDP per capita, industrial production) and other control variables. A positive and significant coefficient on GDP is usually taken to imply that credit growth is dependent on GDP growth and the former is procyclical. In theory, favourable economic conditions boost spending by households and firms. This enhanced spending activity stimulates demand of credit (Hofmann, 2001). In line with theoretical expectations, there has been overwhelming evidence of bank credit growth being procyclical (Hofmann, 2004; Calza et al., 2003; Njoroge and Kamau, 2010). This finding is important for bank regulators because it suggests the need for countercyclical stabilization measures especially when credit booms can be predicted

[8] See, for instance, Barajas et al., (2007); Bakker and Gulde (2010); Ali and Daly (2010); Kiss et al. (2006); Hofmann (2004); Aisen and Franken (2010); Coricelli et al., (2006); Mendoza et al., (2008); Ahmad and Ariff (2007) and many others

[9] See, for instance, Albertazzi and Gambacorta (2009), Bikker and Hu (2002), Bouvatier and Lepetit (2012), Marcucci and Quagliariello (2009), Quagliariello (2007) and many others

beforehand. There is also a possibility of an inverse relationship between credit growth and GDP (Hofmann, 2001). This happens when firms switch from external to internal borrowing during an economic upswing which improves their cashflow position. A shift towards internal funds lowers demand for bank credit.

Apart from GDP growth, other common regressors appearing in loan growth regression are inflation rate, interest rates and public debt (Hofmann, 2001; Calza et al., 2003; Brzoza-Brzezina, 2005; Cottarelli et al., 2005). The GDP growth is usually included in the loan growth regressions to capture business cycle effects while the interest rate proxies the cost of credit in the economy. Inflation is used to capture macroeconomic instability. Public debt is usually used to proxy sovereign risk since high levels of debt may increase the risk that an economy will experience capital flight (Ali and Daly, 2010). A government can always deal with its debt by simply defaulting. The higher the government debt, the greater the temptation of default. External debt tends to be inversely correlated with loan growth. From theory, the effect of inflation on loan growth is indeterminate – it is either positive or negative (Wagner and Winkler, 2013; Chaibi and Ftiti, 2015). The positive effect depends on whether inflation works via the labour market by reducing unemployment as hypothesized by Phillips curve or through an increase in loan servicing capacity due to a fall in the real value of the loan. The negative effect works through a fall in real incomes, which reduces the loan servicing capacity. Interest rate is included in the regressions to capture the cost of credit (Hofmann, 2001). A tight monetary policy evidenced by high interest rates, reduces bank liquidity and the capacity of banks to lend, hence reducing credit supply. Similarly, when the Central bank controls money via open market operations, the lowers reserves and loanable funds which decreases credit supply.

Bank loan growth regressions have also included institutional factors as predictors. Such factors include governance indicators and business environment indicators (Boutriga et al., 2010; Breuer, 2006; Hermes et al., 2011). A few studies have made attempts to capture financial sector reforms, accounting standards, banking sector entry barriers and the origin of the legal system (Cotarelli et al., 2005). Following predictions of new institutional economics theory, it is expected that institutional variables will be positively and significantly correlated with loan growth.

Regarding SSA, banking sector evidence indicates that the market structure of banks, their financial strength and regulatory capital are the broad determinants of lending behaviour (Amidu, 2014) whereas country-level evidence shows that the macroeconomic environment is a significant predictor of lending by banks (Njoroge and Kamau, 2010). Even though there are stark differences between microfinance and banking sectors, evidence from the microfinance markets in this region is lacking.

In terms of modelling, previous microfinance studies (Wagner and Winkler, 2013; Ahlin et al., 2011) on credit growth have assumed static relationships and ignored the dynamics of lending behaviour. They have used static models along with either random-effects or fixed-effects estimators that do not allow one to use observable information of previous periods in the model. Similarly, such estimators are limited in dealing with endogeneity biases that are common in social economic data. Using banking data, authors like Lane and McQuade (2014), Kiss et al., (2006), Amidu (2014), Gambacorta and Mistrulli (2004) and Bouvatier and Lepetit (2012) have captured dynamics in their models. However, most of these studies used a one-way error components model. Bouvatier and Lepetit (2012) expanded these models by using a two-way error components model in which MFI-specific factors and country heterogeneities were controlled for.

This study extends existing knowledge in microfinance in two ways. First, the study uses a dynamic model where loan growth is modelled to depend on its past realizations. The model is estimated using system GMM, which is an estimator that is versatile in dealing with panel endogeneity biases that arise from reverse causality, omitted variables and measurement errors. In addition, the study controls for idiosyncratic factors of the SSA region and provides evidence for a region that has been largely neglected in the relevant literature.

2.3 Methodology and Data

2.3.1 Model Specification

Since this study is using panel data, loan growth, g_{it}, is observed over time, opening up the possibility of estimating parameters of dynamic models that specify the loan growth to depend in part on $g_{i,t-1}, \dots \dots \dots g_{i,t-p}$, which are its values in previous periods (Cameron and Trivedi, 2010). Given this fact, some studies such as Kiss et al. (2006) as well as Lane and McQuade (2014) specify a one-way error components dynamic model which is an autoregressive model of order 1 in g_{it} [an AR (1) model] with $g_{i,t-1}$ as a regressor and ***X*** and ***W*,** as vectors. This specification is shown in equation (1).

$$g_{it} = \alpha_1 g_{i,t-1} + \boldsymbol{X}'_{it}\beta + \boldsymbol{W}'_t\rho + \varepsilon_{it} \qquad (1)$$

$$\varepsilon_{it} = \mu_i + u_{it} \qquad (2)$$

$$where\ i = 1 \dots . N;\ \ t = 1 \dots . T$$

Although panel data contains both cross sectional and time dimensions, equation (1) does not control for time-specific effects. In the studies reviewed in section 2, only Bouvatier and Lepetit (2012) accommodated time-specific effects in their models. Taking this into account, equation (1) is modified by incorporating time-specific effects to give equation (3), which is a two-way error components model.

$$g_{it} = \alpha_1 g_{i,t-1} + \boldsymbol{X}'_{it}\beta + \boldsymbol{W}'_t\rho + \varepsilon_{it} \quad (3)$$

$$\varepsilon_{it} = \mu_i + \lambda_t + u_{it} \quad (4)$$

$$where\ i = 1 \ldots.N;\ t = 1 \ldots.T$$

The regressand g_{it} is loan growth of MFI *i* in year *t*. *Loan growth* (g_{it}) is the log difference in year-end gross loan portfolio. Vector $\boldsymbol{X}_{it}$ contains MFI-level variables, which include *credit risk*, *Herfindahl-Hirschman index*, *capital asset ratio* and *return on equity*. Macro-institutional variables are contained in the vector $\boldsymbol{W}_t$. These variables include *GDP growth, inflation, money supply, regulatory quality and ease of getting credit.* MFI-specific and time-specific fixed effects are captured by μ_i and λ_t respectively while u_{it} is white noise.

In equation (3), g_{it} is correlated over time directly through (i) $g_{i,t-1}$ in preceding periods which is termed true state dependence; (ii) through observables $\boldsymbol{X}_{it}$ and $\boldsymbol{W}_t$, which is termed observable heterogeneity and (iii) indirectly through time invariant individual effect μ_i and time variant effect λ_t, which are collectively termed unobserved heterogeneity. These correlations generate the problem of "dynamic panel bias" (Roodman, 2009). To consistently estimate α, β and ρ, for time varying regressors, μ_i can be eliminated by appropriate differencing transformation[10].

[10] $\Delta g_{it} = \alpha_1 \Delta g_{i,t-1} + \Delta\boldsymbol{X}'_{it}\beta + \Delta\boldsymbol{W}'_t\rho + \Delta\varepsilon_{it} \quad where \quad \Delta\varepsilon_{it} = \Delta u_{it} + \Delta\lambda_t$

First differencing transformations are not enough to deal with endogeneity biases and an application of OLS on equation (3) will produce inconsistent parameter estimates because the lagged term [$\Delta g_{i,t-1}$] is correlated with the error Δu_{it}, even if u_{it} is serially uncorrelated. This correlation provides justification for the use of instrumental variable estimation where lagged dependent variables and exogenous variables enter as instruments as proposed by Anderson and Hsiao (1981). However, more efficient instrumental variable estimators termed Arellano-Bond estimators can be obtained by using more lags of the dependent variable as instruments (Holtz-Eakin et al., 1988). According to Cameron and Trivedi (2010), the Arellano-Bond estimator assumes that $E(g_{it}\Delta u_{it}) = 0$ for $s \leq t\text{-}2$ so that the lags $g_{i,t-2}, g_{i,t-3}, \ldots \ldots$ can be used as instruments in the first differenced model.

According to Arellano and Bover (1995) and Blundell and Bond (1998), it is possible to obtain another estimator which is more precise and which exhibits better finite sample properties. This can be implemented by imposing an additional condition $E(\Delta g_{i,t-1} u_{it}) = 0$ so that the levels (equation 3) can be incorporated and $\Delta g_{i,t-1}$ can serve as instruments. This builds a system of two equations where the equation in levels applies lagged first differences as instruments while the equation in first differences applies lagged levels as instruments. Adapting this approach, this study will apply the two-step GMM version of the Arellano and Bover (1995) and Blundell and Bond (1998) extensions which accommodate unobserved heterogeneity as well as endogeneity.

2.3.2 Data Description and Sources

Data was assembled from four sources – MIX dataset of the Microfinance Information eXchange (www.mixmarket.org) and World Development Indicators, World Governance Indicators and Doing Business Indicators datasets of the World Bank. The MIX data is merged with country-level data from the World Development Indicators, Doing Business Indicators and World Governance Indicators. The data used for this study covers the period 2004-2014.

The MIX dataset is a global unbalanced MFI-level panel. The number of MFIs in the sample over the 2004-2014 period is 2687 for the global sample but 745 for SSA, 393 for East Asia and the Pacific (EAP), 483 for Eastern Europe and Central Asia (EECA), 562 for Latin America and the Caribbean (LAC), 423 for South Asia (SA) and 80 for Middle East and North Africa (MENA). Regarding the number of observations, the total sample has 16,383 observations distributed regionally as follows: SSA (3122), SA (2379), LAC (3898), EECA (2592), EAP (1833) and MENA (559). The sample covers 120 countries, which are listed in Appendix Table A3. The sample includes 37 countries from SSA, 16 from EAP, 24 from EECA, 26 from LAC, 10 from MENA and 7 from SA.

2.3.3 Definition and Measurement of Variables

The dependent variable, *loan growth* is the log difference in year-end gross loan portfolio (gross loan portfolio represents total amount of all loans outstanding). All MFI-specific variables are drawn from the MIX dataset. Four MFI-level variables are used: lagged *loan growth*, *credit risk*, *capital asset ratio* and *return on equity*. In addition, the level of market concentration in the MFI sector is proxied by the Herfindahl-Hirschman index (Basega-Pascual et al., 2015; Wagner and Winkler, 2013). It is computed using the following formula; $HHI = \sum_{i=1}^{n} S_i^2$ where S_i is the market share of firm *i* in total *n* firms in the country being considered. The effect of competition on loan growth is mixed. High competition in a saturated market adversely affects loan growth. However, higher competition can also mean higher efficiency in the delivery of loans.

Lagged *loan growth* is used to capture persistence in loan growth over time or conditional convergence. Ideally, *loan growth* at time *t* contains some information from its previous values $(g_{t-1}, \dots . g_{t-p})$. Due to persistence in loan growth, the value of loan growth in previous periods is expected to predict the current level of loan growth (Lane and McQuade, 2014). The coefficient on lagged loan growth indicates the speed at which the loan growth reverts to the long-run equilibrium (Chikalipah, 2018). Literature on conditional convergence (see Fung, 2009; Asongu, 2013; Asongu and Nwachukwu, 2016) suggests that convergence is established when two criteria are met. Firstly, α_1 should be statistically significant. Secondly, the absolute value of the estimated coefficient on the lagged dependent variable should be within the interval of zero and one ($0<|\alpha_1|<1$). However, the speed of convergence can be derived by subtracting 1 from the estimated coefficient on the lagged dependent variable $(\alpha_1 - 1)$.

Credit risk is measured as the sum of portfolio at risk and the write-off ratio (Gonzalez, 2011; Wagner and Winkler, 2013; Sinkey and Greenwalt, 1991). Portfolio at risk is the proportion of loans in the gross loan portfolio of an MFI that has been overdue for more than 30 days while the write-off ratio is the share of loans in the portfolio that are written off. *Credit risk* measures the quality of an MFI's loan portfolio and gives the probability that the MFI loan assets will suffer from default. The relationship between credit risk and loan growth is embedded in the real business cycle theory which postulates that MFIs will suffer a high default risk due to reduced household and firm earnings during a recession. In response to increased risk exposure, MFIs tend to reduce lending by raising the credit standards and lending rates of interest in order to minimize further likelihood of default. Thus, it is expected that there will be a negative relationship between *credit risk* and *loan growth*.

Capital asset ratio is the proportion of total equity in total assets. It is used to account for an MFI's stability (Amidu, 2014). A higher capital asset ratio boosts an MFI's solvency, meaning that it holds a sufficient capital buffer to support its assets. According to Mishkin (2013), a highly capitalised firm faces less risk exposure because the owners have an incentive to pursue less risky ventures. It does this by becoming more stringent in underwriting loans and monitoring them, which reduces lending growth but minimizes loan default. Therefore, it is expected that there will be an inverse relationship between the *capital asset ratio* and *loan growth*.

Return on equity is a proxy for management efficiency (Love and Ariss, 2014). It is expected that correlation between loan growth and return on equity will be either positive or negative. Efficiency in lending may lead to a decrease in loan growth in view of the lemons problem. *Return on equity* can also be associated with an increase in lending if profitability is associated with an economic upswing combined with an increase in demand for credit.

This study considers three macroeconomic variables, which are drawn from the World Development Indicators database of the World Bank. These variables are *GDP growth, inflation* and *money supply*. Following Ahlin et al. (2011) and Wagner and Winkler (2013), this study controls for *GDP growth*, which is measured as the annual percentage change in real GDP per capita. *GDP growth* captures business cycle effects. Both business cycle theory and evidence support procyclicality between economic expansion and lending growth (Hofmann, 2001; Calza et al., 2003; Njoroge and Kamau, 2010; Ahlin et al., 2011).

Inflation is measured by the annual percentage change in the consumer price index (CPI). The effect of *inflation* on *loan growth* is ambiguous. The positive effect works via two channels. The first channel is based on the Phillip curve hypothesis, which postulates an inverse relationship between *inflation* and unemployment. Higher *inflation* is associated with lower unemployment and higher capacity to service loans. The second channel works through the effect of *inflation* on the real value of the loan. The real value of the loan tends to fall when inflation is high (Wagner and Winkler, 2013). High *inflation* can also adversely affect *loan growth*. This occurs because high inflation reduces real incomes and therefore adversely affects loan servicing ability (Chaibi and Ftiti, 2014).

Money supply is broad money (M3) as a percentage of GDP. It is used to capture financial sector depth or the size of the financial sector (Wagner and Winkler, 2013). The relationship between *loan growth* and financial depth is mixed (Ahlin et al. 2011). Demand for microcredit may fall where financial development opens up opportunities for microentrepreneurs in formal financial institutions. Conversely, MFIs might be pushed by the developed banking sector to lend to the micro-entrepreneurs.

Two institutional variables are used in this study: *regulatory quality* (drawn from the World Governance Indicators of the World Bank) and *ease of getting credit* (drawn from Doing Business Indicators of the World Bank). It is expected that these indicators will have a positive correlation with loan growth because good institutions have been hypothesized to smoothen the functioning of factor and product markets as well as the operations of the state (McMullen et al., 2008; North, 1990; Ahlin et al. 2011). *Regulatory quality* is a perception index ranging from -2.5 (weak governance performance) to +2.5 (strong governance performance). It measures "the ability of the government to formulate and implement sound policies and regulations that accelerate the development of the private sector" (Indicators, 2015). *Ease of getting credit is* measured in terms of distance to the frontier on a 0 to 100 scale. It measures "the legal rights of borrowers and lenders with respect to secured transactions and the reporting of credit information" (Business, 2017).

2.4 Empirical Results

2.4.1 Descriptive Statistics

Results in Appendix Table A5 indicate that most of the variables are not normally distributed since their skewness and kurtosis values are at variance with the conventional skewness of 0 and kurtosis of 3 for a normal distribution. The skewness and kurtosis values for loan growth are 3 and 26, respectively implying that the distribution is positively skewed with fat tails. That means the error term in equation (3) is also likely to be non-normal. In view of this, GMM estimators are deployed to allow reliable estimation of the parameters when the distribution of the error term is not normal.

Table 1 indicates that there are significant mean differences between SSA and non-SSA regarding loan growth, market concentration, GDP growth, inflation, regulatory quality and ease of getting credit. The macroeconomic and institutional environment in SSA countries lags behind the environment existing in non-SSA countries. Relative to non-SSA, economic growth is lower and inflation higher in SSA while regulatory quality is poorer and getting credit more difficult.

Table 1: Comparisons – SSA and non-SSA

	Non-SSA	SSA	Difference	t-ratio
Loan growth (ratio)	0.26	0.29	-0.026*	(-2.14)
Credit risk (ratio)	0.31	0.12	0.192	(0.51)
Mkt concentration (index)	0.03	0.06	-0.03***	(-29.79)
Capital asset ratio	0.35	0.32	0.034	(1.32)
Return on equity (ratio)	0.15	-0.09	0.236	(0.32)
Money supply (%)	22.4	28.5	-6.11	(-0.92)
GDP growth (%)	4.55	2.58	1.97***	(25.40)
Inflation (%)	4.96	7.79	-2.83***	(-9.73)
Regulatory quality (index)	-0.34	-0.50	0.16***	(16.34)
Ease of getting credit (index)	43.6	33.08	10.5***	(24.04)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1 shows that the pace of loan growth is faster in SSA countries compared to non-SSA countries. This pace of loan growth is not only essential for sustainability but is also an indicator of positive impact. The loan growth rate of 29% is considered to be fairly high. At the country level, however, the rate of loan growth in microfinance markets is far from uniform (see Appendix Table A4). The top five loan growth markets include Guinea Bissau, Namibia, Democratic Republic of Congo, Gabon and Gambia. However, receding markets include Comoros and Zimbabwe.

Results presented in Appendix Table A4 show that an average MFI in SSA is loss-making while an average MFI in non-SSA regions is profit-making. Almost 50% of the countries in SSA record negative profits. Perhaps MFIs in SSA deploy microfinance assets to pursue their social mission rather than achieve financial sustainability. On a positive note, about 32.4% and 35% of microfinance assets are supported by capital in SSA and non-SSA respectively. This reflects some financial stability given that the threshold is 12%, owing to the more volatile and riskier environments in which MFIs operate (Berger, 2010).

2.4.2 Regression Results

Before performing regression analysis (whose results are reported in Tables 2 and 3), the data was checked for collinearity among explanatory variables by computing the correlation matrix (see Appendix Table A6). All the correlation coefficients are small (less than 0.5) implying that multicollinearity is not a problem. After running the regressions, the results were checked for proper specification by applying the Arellano-Bond test for zero autocorrelation in the differenced errors and the F-test for joint significance of the coefficients. All the regressions are statistically significant at 1%. Considering AR (1), the p-values are below 0.10 except in the regression for EAP while a look at the AR (2) shows that the associated p-values exceed 0.10 except in the regression for EECA. These AR (1) and AR (2) tests imply that the null hypothesis of no autocorrelation cannot be rejected. When implementing the AR test, the statistical significance of the AR (1) is not the main focus because the model has been designed to allow autocorrelated errors (Roodman, 2009). However, the focus is on AR (2), which is supposed to be independent of the regressors. Almost all the regressions satisfy the AR (2) test.

2.4.2.1 Determinants of Loan Growth in SSA: Baseline Model

The primary focus of this study is to identify the factors that significantly explain differences in loan growth between 2004 and 2014. However, the sample is broken down into two periods (2004-2008 and 2009-2014) to correspond to phases of high loan growth (37% per year) and phases of low loan growth (16% per year) (see Appendix Figure A1 Panel A).

Table 2: Determinants of loan growth in SSA – Baseline results

	Dependent variable: log loan growth		
	2004-2014	2004-2008	2009-2014
Log loan growth (L1)	**0.04*** **	**0.11** **	**-0.03** **
	(0.013)	(0.044)	(0.014)
Credit risk	**-0.79*** **	**-0.62*** **	**-0.73*** **
	(0.033)	(0.067)	(0.099)
Mkt concentration	-0.45	-13.40	**3.87*** **
	(0.604)	(14.732)	(1.028)
Capital asset ratio	**0.10** **	0.19	-0.05
	(0.049)	(0.120)	(0.106)
Return on equity	0.02	**0.13*** **	-0.01
	(0.013)	(0.014)	(0.015)
Money supply	-0.00	-0.00	-0.00
	(0.002)	(0.006)	(0.002)
GDP growth	**0.01*** **	0.01	**0.01*** **
	(0.001)	(0.008)	(0.002)
Inflation	-0.00	**-0.01*** **	**0.01*** **
	(0.001)	(0.003)	(0.001)
Regulatory quality	**0.15*** **	**-0.76*** **	**0.38*** **
	(0.037)	(0.245)	(0.055)
Ease of getting credit	**-0.00*** **	-0.01	**0.00*** **
	(0.000)	(0.017)	(0.001)
No of observations	712	361	351
Wald Chi2	0.00	0.00	0.00
AR(1) [p-value]	0.002	0.063	0.005
AR(2) [p-value]	0.159	0.204	0.88
Sargan [p-value]	0.778	0.349	0.70

The dependent variable is loan growth (in logs). Endogenous variable is lagged loan growth while the rest of the variables are treated as exogenous. Two-step system GMM estimator, standard errors (in parentheses) and small-sample adjustments were applied. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Results for Arellano-Bond test for zero autocorrelation in first differenced errors (H_0=there is no autocorrelation) and Wald-Chi2 test for joint significance of parameters are reported. Results of Sargan test for overidentifying restrictions (H_0=overidentifying restrictions are valid) are also reported. (L1) indicates the first lag. Time dummies are included in the regression but not reported.

Baseline results show that micro-level, macroeconomic and institutional factors are significant predictors of loan growth in SSA not only between 2004 and 2014 but also during the 2004-2008 period and the 2009-2014 period. Predictors of loan growth for the entire period (2004-2014) include lagged loan growth, credit risk, capital asset ratio, GDP growth, regulatory quality and the ease of getting credit.

During 2004-2014, loan growth in MFIs is higher when credit risk and the ease of getting credit are lower and when capitalisation, GDP growth and regulatory quality are higher. However, a comparison of the results for the 2004-2008 and the 2009-2014 period reveals three relationships. The first finding is that the factors that were statistically significant during the 2004-2008 period do not necessarily remain statistically significant during the 2009-2014 period. Secondly, four variables, namely, lagged loan growth, credit risk, inflation and regulatory quality were statistically significant during both periods. However, inflation, regulatory quality and lagged loan growth reversed their signs over the two periods. The third finding is that market concentration, GDP growth and ease of getting credit, which were not significant during 2004-2008, became significant during 2009-2014 while return on equity was statistically significant during 2004-2008 but became insignificant during 2009-20014. This suggests that the explanatory factors change when the loan growth phases change.

Tests for conditional convergence show that loan growth is persistent. Testing for conditional convergence requires the fulfilment of two criteria (see Fung, 2009; Asongu, 2013; Asongu and Nwachukwu, 2016). First, the estimated coefficient on lagged loan growth should be statistically significant. Lastly, the absolute value of the estimated coefficient on lagged loan growth should lie between zero and one. The results in Table 2 suggest that the coefficients on lagged loan growth satisfy these two criteria during all the different periods analysed. A 1% increase in past loan growth is associated with a 0.04% increase in current loan growth during the 2004-2014 period. This indicates that loan growth over this period was higher among those MFIs that were already having high loan growth rates. The same persistence is evident during 2004-2008 and 2009-2014. These findings imply that dynamics matter for loan growth in MFIs. After experiencing a fast growth in loans in the past, rational MFI managers increased growth in their lending, especially if increased lending was driven by demand-shifts in the economy. However, when lending is driven by supply-shifts in the credit markets, it is likely to result in low quality loans. The same thing happens if growth in lending is associated with weak monitoring capacity, it also results in low quality loans and will lower future lending as the lenders become more stringent.

Credit risk is statistically significant with a negative sign. A one-unit increase in credit risk lowers loan growth by 79% during 2004 – 2014, 62% during 2004-2008 and 73% during 2009-2014. This result is consistent with the findings by Wagner and Winkler (2013) and confirms a trade-off between loan growth and risk so that MFIs that face more risk lend much less. This is explained by risk-averse behaviour among managers of MFIs as they respond to adverse selection and moral hazard in lending. Falling loan quality is accompanied by a more conservative loan strategy by MFI management. MFI managers find it rational to tighten lending, showing less willingness to either advance new loans or renew existing loans. This can be achieved by raising underwriting standards, which deters new loans to customers.

Capital asset ratio has a positive and significant effect on loan growth during 2004-2014. This suggests that more capitalised MFIs tend to adopt an aggressive lending policy because they can achieve efficient scales of operations that are not feasible for less capitalised MFIs (Clair, 1992). Effectively, an increase in the capital asset ratio by one unit increases loan growth by 10%. Surprisingly, the capital asset ratio does not remain statistically significant when the data is broken down into two periods (2004-2008 and 2009-2014). This means the role of this variable depends on the period under consideration.

Evidence supports procyclicality between economic upswings and lending growth in MFIs (Hofmann, 2004; Calza et al., 2003; Ahlin et al., 2011). This relationship is clear during 2004-2014 and 2009-2014 but is not detected during 2004-2008. The results show that a one-unit increase in GDP growth is associated with a 1% increase in loan growth. This is attributed to increased demand for loans which follows increases in economy-wide aggregate demand.

Results for 2004-2014 show that political and business institutions provide a conducive environment for lending but they also hinder lending growth by MFIs suggesting that the effect of institutions on credit growth is ambiguous. Better regulatory quality predicts higher loan growth whereas ease of getting credit predicts slower lending growth during 2008-2014. This suggests that reforms that have sought to promote legal rights of borrowers and lenders with respect to secured transactions and the reporting of credit information have instead made it costlier for MFIs to increase lending in a fully compliant way (Ahlin et al., 2011). There is a possibility that such reforms are generating better opportunities outside the micro-credit sector, which reduces the dependence on MFI services and weakens loan growth in MFIs.

2.4.2.2 A Global Analysis of Loan Growth Determinants

This section compares results for the loan growth determinants in SSA countries to those in other regions (Table 3). The comparisons are meant to determine whether these factors are important predictors of loan growth differences in other regions (EAP, EECA, LAC, SA). These comparisons are useful because explanations for loan growth that are supported by empirical evidence in one region may not apply in other regions.

Table 3: Determinants of loan growth – International comparisons

	Dependent variable: log loan growth					
	SSA	EAP	EECA	LA	SA	World
Log loan growth (L1)	**0.04*** **	**-0.02*** **	**0.15*** **	**0.09*** **	**0.22*** **	**0.12*** **
	(0.013)	(0.004)	(0.009)	(0.007)	(0.015)	(0.013)
Credit risk	**-0.79*** **	**-0.31*** **	**0.00*** **	**-1.51*** **	**-0.21** **	**0.00*** **
	(0.033)	(0.054)	(0.000)	(0.059)	(0.096)	(0.000)
Mkt concentration	-0.45	**-1.40*** **	**-5.08*** **	-2.75	**16.47** **	-12.72
	(0.604)	(0.428)	(1.054)	(2.370)	(6.512)	(14.611)
Capital asset ratio	**0.10** **	**-0.54*** **	**-0.11* **	**-0.50*** **	0.06	-0.03
	(0.049)	(0.032)	(0.060)	(0.040)	(0.057)	(0.035)
Return on equity	0.02	**0.01** **	0.01	**-0.03*** **	**-0.00*** **	**-0.01*** **
	(0.013)	(0.003)	(0.021)	(0.006)	(0.000)	(0.000)
Money supply	-0.00	**0.00*** **	**-0.01*** **	**0.00* **	**-0.01*** **	**-0.01*** **
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
GDP growth	**0.01*** **	**0.01*** **	**0.00** **	**0.00** **	0.00	**0.01*** **
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)
Inflation	-0.00	**0.03*** **	-0.00	**0.02*** **	**0.01*** **	**0.01*** **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Regulatory quality	**0.15*** **	**-0.58*** **	**0.41*** **	**0.20*** **	**0.43** **	0.06
	(0.037)	(0.034)	(0.043)	(0.015)	(0.172)	(0.053)
Ease of getting credit	**-0.00*** **	0.00	**-0.00*** **	0.00	0.00	**-0.00** **
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
No of observations	712	677	747	1,793	1,271	5,359
Wald chi2[p-value]	0.00	0.00	0.00	0.00	0.00	0.00
AR (1) [p-value]	0.002	0.709	0.00	0.00	0.001	0.00
AR (2) [p-value]	0.159	0.208	0.021	0.274	0.503	0.758
Sargan [p-value]	0.778	0.999	0.854	0.268	0.98	0.063

The dependent variable is log loan growth. Endogenous variable is lagged loan growth while the rest of the variables are treated as exogenous. Two-step system GMM estimators, standard errors (in parentheses) and small-sample adjustments were applied. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Results for Arellano-Bond test for zero autocorrelation in first differenced errors (H_0=there is no autocorrelation) and Wald Chi2 test for joint significance of parameters are reported. Sargan test for overidentifying restrictions (H_0=overidentifying restrictions are valid) is also reported. (L1) indicates the first lag. All region-specific regressions include time dummies but the regression for World includes both time effects and regional effects. A constant is not included in the regressions. Results for MENA are excluded due to few observations.

The following observations stand out from Table 3. Firstly, the results indicate that dynamics matter for loan growth globally and in all regions. Persistence of loan growth is highest in SA where a 1% increase in past loan growth is associated with 0.22% increase in current loan growth. In EECA, a past loan growth of 1% is associated with a 0.15% increase in current loan growth. LA (0.9%) and SSA (0.4%). In these regions, loan growth was higher among those MFIs where loan growth was already high.

The second notable observation is that micro-level, macroeconomic and institutional factors are significant predictors of loan growth in all regions. However, specific factors that significantly affect loan growth in SSA do not remain statistically significant in the models for EAP, EECA, LAC and SA. Only two factors significantly predict loan growth in all regions: credit risk and regulatory quality. The remaining factors differ by region. For example, in SSA, loan growth is higher in MFIs that are highly capitalised and those that operate in countries with higher economic growth and ease of getting credit index. Loan growth in EAP is driven by market concentration, capital asset ratio, return on equity, money supply, GDP growth and inflation. In EECA, it is market concentration, capital asset ratio, money supply, GDP growth and ease of getting credit that influence loan growth while the following factors determine loan growth in LAC: capital asset ratio, return on equity, money supply, GDP growth and inflation. Loan growth in SA is driven by market concentration, return on equity, money supply and inflation. At the global level, it is return on equity, money supply, GDP growth, inflation and ease of getting credit that explain variations in loan growth. These differences in explanatory factors are driven by regional heterogeneity and suggest the need for region-specific microcredit outreach interventions.

Finally, the fact that GDP growth and money supply are statistically significant in four out of the five regions (and globally) implies that these are the key avenues through which macroeconomic shocks are transmitted to the balance sheets of MFIs (via stocks of gross loan portfolio). In terms of policy, this implies that monetary policy and other policies affecting aggregate demand could be applied to manage instabilities in the MFI sector.

2.5 Conclusion and Policy Recommendations

While there has been some research effort toward understanding the key drivers of the rapid growth in lending recorded in microfinance markets, existing knowledge is inconclusive and limited. As such, the aim of this chapter was twofold: to identify the factors that determine loan growth differences in SSA and to explore whether any international differences exist in the way such factors affect loan growth. To achieve these two objectives, data was assembled from the MIX database, World Development Indicators, World Governance Indicators database and Doing Business Indicators database. This data was merged and used to run regression equations applying system GMM estimators.

The results show that micro-level, macroeconomic and institutional factors are significant predictors of loan growth in SSA over the period 2004-2014. Specific factors that explain variations in loan growth include lagged loan growth, credit risk, capital asset ratio, GDP growth, regulatory quality and the ease of getting credit. This study has also confirmed that the factors that significantly affect loan growth in SSA do not remain statistically significant in regression equations for EAP, EECA, LAC and SA. These differences in explanatory factors suggests that interventions designed and directed to spur the expansion of microcredit should be region-specific and should focus on the most important factors in each region.

Five key recommendations can be drawn from the study's findings. Overwhelming evidence suggests that dynamics matter for loan growth in all regions, implying that loan growth is persistent. Credit management methodologies can be revised accordingly, as credit scoring, credit appraisals and other processes that incorporate past loan performance in their current loan projections are likely to perform better.

The second recommendation is based on the finding that credit risk is negatively associated with loan growth in SSA and in all other regions. This implies that there is a trade-off between growth in lending and the accumulation of non-performing loans. Since MFI managers are risk-averse, high volumes of non-performing loans may push them to tighten lending standards. Regulators should encourage MFIs to efficiently manage their loan portfolios because this lowers their risk exposure and boosts lending activity.

Thirdly, the level of capitalisation is associated with higher lending growth because MFIs with high capital asset ratios are more stable. In other words, such MFIs hold sufficient capital to support their assets. In terms of policy, this finding implies that the level of capitalisation affects loan growth and can be used as a prudential regulation tool to control lending in MFIs, as is the case in the banking industry.

Fourthly, the fact that GDP growth and money supply are statistically significant in four out of the five regions (and globally) implies that these two factors are potential channels through which macroeconomic shocks are transmitted to the balance sheets of MFIs (via stocks of gross loan portfolio). As such, MFIs are sensitive to monetary policy impulses and other policies affecting aggregate demand. This finding supports the recommendation that monetary policies can be applied to mitigate instabilities in the MFI sector.

Finally, this study found that the effect of institutional factors on loan growth is ambiguous. This suggests that the impact of institutional reforms on lending in MFIs may not be predictable beforehand, and also implies that the effects of such reforms may negate the expected outcomes. To remedy such situations, institutional reforms should be well sequenced so that complementarities and conflicts among their different components are ironed out to maximize their anticipated positive impact.

Chapter 3

Determinants of Credit Risk in Sub-Saharan Africa Microfinance Institutions

3.1 Introduction

Financial distress facing microfinance institutions (MFIs) in sub-Saharan Africa (SSA) and in other regions of the world has elicited concerns regarding the financial health of the microfinance sector. Riquet and Poursat (2013) reported that between 2001 and 2011, 25 MFIs in WAEMU[11] and four in CEMAC[12] were placed in temporary government administration[13]. Pride Zambia (Zambia) and African Bank (South Africa) — some of the largest MFIs in their countries - collapsed in 2009 and 2014, respectively. In Morocco, a loan growth of 59% between 2004 and 2008 resulted in 12 MFIs facing loan delinquency as portfolio at risk rose from 6% in 2008 to 10% in 2009. In the first quarter of 2013, up to 30 MFIs collapsed in Ghana and later in the year, an additional 20 also became insolvent (Boateng et al., 2016). All these episodes of ailing and failing microfinance institutions reveal a rising trend of financial crises in microfinance markets in SSA. This has been attributed to excessive market growth, insufficient institutional capabilities, predatory lending, systemic fraud, loss of focus, design

[11] West African Economic Monetary Union (WAEMU) comprises eight countries: Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo.
[12] Economic and Monetary Community of Central Africa (CEMAC) comprises six countries: Cameroon, Central African Republic, Congo, Gabon, Equatorial Guinea, and Chad.
[13] Temporary government administration (TGA) is imposed by regulators when the poor management of a financial institution threatens its financial health and/or the interests of its clients, especially depositors (Riquet and Poursat, 2013).

flaws and overzealous government intervention (Lutzenkirchen and Weistroffer, 2012; Marulanda et al., 2010).

The level of credit risk in MFIs has been trending upwards. Median credit risk rose from around 3.6% in 2000 to 8.2% in 2010, after which there was a slight reversal of the trend (see Appendix Figure A2 Panel A). Appendix Figure A2 Panel B shows that there has been notable variability in microcredit risk. The highest standard deviation of 22% was recorded in 2002, which implies that the difference between the observed risk levels and the mean risk in that year was about 22% on average.

Given these episodes of MFI collapse and increasing portfolio risk, examining the drivers of credit risk in these institutions has become a key issue for regulators (local and international), microfinance practitioners and researchers. At the global level, there has been limited research interest in understanding the determinants of credit risk in microfinance markets. Earlier attempts focused on the relationship between credit risk, on one hand, and on the other hand: group lending methodology (Crabb and Keller, 2006), macroeconomic shocks (Gonzalez, 2007), the gender factor (Schmit and Marrez, 2010; and D'espallier et al., 2011), the excessiveness of loan growth (Gonzalez, 2010) and loan size (Chikalipah, 2018). More recent efforts towards understanding credit risk determinants are by Sainz-Fernandez et al. (2015) and Yimga (2016), who conducted more comprehensive analyses of credit risk in MFIs. However, the study by Sainz-Fernandez et al. (2015) specifies static relationships which do not account for dynamic aspects of credit risk while Yimga's (2016) dynamic study does not control for institutional factors. Except for Chikalipah (2018), existing knowledge does not focus on microfinance on SSA yet the median credit risk is significantly higher in SSA compared to other regions. Appendix Figure A3 shows that between 2000 and 2014, median credit risk is 7.1% in SSA while it is 6.6% in LAC, 4.3% in EAP, 3.2% in MENA, 2.9% in EECA and 2.0% in SA. The study by Chikalipah (2018) fails to account for macro-institutional environment yet there exists both theoretical (North, 1990; McMullen et al., 2008) and empirical (Ahlin et al., 2017) evidence supporting the link between macro-institutional factors and performance of firms. Similarly, most past studies applied random effects and fixed effects estimators without controlling for endogeneity, which arises due to reverse causality, omitted variables and measurement errors. The studies did not test for non-linearities in the relationship between credit risk and loan growth.

Given the preceding shortfalls in the existing literature, the purpose of this study is to identify both micro-level and macro-institutional determinants of credit risk in MFIs in SSA and establish whether these factors have heterogenous effects on credit risk in other regions of the world. The study contributes to microfinance literature by not only documenting determinants of loan risk in SSA but also by identifying predictors of credit risk in Latin America and the Caribbean (LAC), Eastern Europe and Central Asia (EECA), Middle East and Northern Africa (MENA) and South Asia (SA). In addition, the study captures the dynamics of credit risk by dynamic generalised method of moments (GMM) estimators, which deal with dynamic panel bias (Roodman, 2009). It extends the evidence on the relationship between credit risk and loan growth by identifying the tipping pints in this relationship.

Findings from this study suggest that the main determinants of risk in SSA are lagged credit risk, loan growth, provision for loan impairment, GDP per capita growth and ease of getting credit. In addition, the study finds that the effect of loan growth on credit risk in SSA is non-linear so that loan growth rates below 36.8% are associated with increased credit quality but loan growth rates above 36.8% contribute to falling loan quality in SSA. Although lagged credit risk, loan growth and provision for loan impairment significantly affect credit risk in all regions, the magnitudes of the effects vary by region. The results show that some factors are more important in some regions than in others. For example, GDP per capita growth is only important in reducing credit risk in SSA, EECA and LAC whereas inflation is only important in enhancing credit risk in EAP and SA. Results also reveal divergencies in the turning points across the regions regarding the non-linear relationship between credit risk and loan growth. EAP reports the turning point at 363%, EECA at 164% and LAC at 108%.

After providing the foremost motivation for the study in this Section, this paper continues with a literature review of credit risk determinants in Section 3.2. In Section 3.3, the empirical model is specified and data is described. Section 3.4 provides the regression results, which is followed by concluding remarks in Section 3.5.

3.2 Literature Review

3.2.1 Theoretical Literature

A review of the theoretical literature identifies the drivers of credit risk as microeconomic factors (principal-agent model), macroeconomic factors (financial accelerator theory) and institutional factors (new institutional economics). Principal-agent model is based on the neoclassical theory, which considers financial institutions as intermediaries of funds between surplus units (lender – savers) and deficit units (borrower-investors) (Freixas and Xavier, 2008; Mishkin, 2013). This function of financial intermediaries is unique for three reasons. Firstly, loan contracts are heterogeneously designed to reflect the quality of the borrowers (Kimuyu and Omiti, 2000). Secondly, exchange involves making intertemporal consumption decisions (Kimuyu and Omiti, 2000). Lastly, exchange is exposed to the “lemons problem” due to the presence of financial frictions and transaction costs (Joshi, 2005; Stiglitz and Weiss, 1981). Given these features of financial markets, the shareholders (principal-owners), who are the owners of the financial intermediary (hereafter, referred to as FI) delegate the day-to-day decision making to the manager (the agent - manager) and give out loans to borrowers (agent-borrowers).

Agency theory suggests that rational agent-managers will pursue self-interest in order to fulfil their utility maximization objective whereas the objective of the principal-owners is to maximize FI value (Jensen and Meckling, 1976). Agent-managers are minority shareholders with less than 100% of residual claims. Motivated by adverse incentives, agent-managers exercise their power for personal gain. In doing so, adverse selection and moral hazard costs arise since agent-managers have incentives to hide information regarding their risk attitude, their goals as well as the feasibility of their projects (Stiglitz and Weiss, 1981) even though it is either impractical or impossible for the principal-owners to verify these attitudes, goals and project feasibility. These levels of interaction expose the FI to principal-agent conflicts, as well as to adverse selection, moral hazard and incentive problems.

The existence of agency costs implies that the actions of the agent-manager will affect FI riskiness through three main channels: free cash flows, debt overhang and asset substitution (Jensen and Meckling, 1976; Schleifer and Vishny, 1989 and Baker and Wurgler, 2002). Whenever there are free cash flows, the agent-manager will invest profit in wasteful ventures such as perks and empire building. This behaviour destroys the value of the FI. Low value of the FI lowers its net worth and with it its debt servicing capacity. Ultimately, the FI's insolvency is increased. The debt overhang channel works when the agent-manager gives out more loans to highly indebted customers or engages in excessive lending behaviour. This has the effect of increasing the default rate and the FI's riskiness. Lastly, the manager can invest in negative net present value (NPV) rather than positive NPV projects. Over time, this has an adverse effect on the FI's share price.

The trade-off theory postulates that self-interested agent-managers tend to favour a low leverage policy because issues of outside equity invite financial slack and lower the disciplining effect of debt (Graham, 1996, 2000; Wald, 1999 and Myers, 1984). This is explained by the relatively lower risk that accompanies issues of equity compared to issues of debt as the latter increases the exposure of the FI to financial distress and requires higher interest rates to compensate for the additional risk. Therefore, the pursuit of a low leverage policy implicitly reflects the existence of moral hazard.

Agency problems also arise during the negotiation of loan contracts between the agent-manager and the agent-borrower. According to Armendariz and Murdoch (2010), these informational problems arise at three levels: before extending the loan, once the loan has been granted and once the business returns have materialized. Before extending the loan, the agent-manager has no way of knowing the quality of the borrower, and there is sufficient risk that the agent-borrower may turn out to be a low-quality borrower. This breeds the adverse selection problem for the agent-manager. Once the loan has been extended, monitoring difficulties will make it difficult for the agent-manager to know whether the agent-borrower will put the loan to good use and whether the loan will be diverted towards unproductive investments. This generates the moral hazard problem for the agent-manager. After the project has yielded returns, the agent-manager has no way of verifying the amount of project returns but the agent-borrower has an incentive to hide the true level of returns thus exposing the former to adverse section problems.

Business cycle movements generate boom-bust cycles that amplify correlations between risk and loan growth (Clair, 1992; Keeton, 1999; Bernanke et al., 1994). Economic upswings are accompanied with better economic conditions, better prospects, higher consumption and investment (Hofmann, 2004). The financial accelerator theory argues that good economic prospects increase bank lending because firm profits and assets rise during an upward swing.

This results in higher household and firm indebtedness as credit standards decline while interest rates fall in response to optimistic customer expectations. However, a reversal in economic prospects leads to an accumulation of non-performing loans since many debtors are likely to default on their loans.

New institutional economics hypothesizes a positive effect of institutions in smoothening the functioning of factor (labour and capital) and product markets as well as the operations of the state (McMullen et al., 2008; North, 1990; Ahlin et al. 2011). The most common institutional variables appearing in the literature include voice and accountability, political stability, government effectiveness, regulatory quality, control of corruption and rule of law. Rule of law measures the level to which citizens trust societal rules and agree to be bound by them, as they relate to the enforcement of contracts, property rights, the police service and the judiciary (Indicators, 2015). Once a society becomes accustomed to obeying laws, it will also find itself similarly accustomed to honouring loan obligations (Breuer, 2006). This leads to mutual interest in the actions of both banks and borrowers implying that problem loans will be lower.

Government stability is associated with application of rules and regulations that can be predicted in advance and a political environment that is more certain (World Bank, 2016). When this is the case, lenders and borrowers have no room to gamble by acting outside those rules and regulations because the implication of their actions can be known in advance (Breuer, 2006). Returns to investment and employment will be certain – improving planning for loan servicing and loan repayment. Bad loans will be lower in such countries. Voice and accountability capture the extent to which a country's citizens are free to vote, to express themselves and to associate. This implies that rules, regulations and policies that emanate from MFIs and other financial intermediaries will be a product of consultative processes and information sharing, which minimizes conflicts of interest. Such an environment lowers the incidence of bad loans in the financial system.

Government effectiveness captures the commitment by government to independently design and implement public programmes. Commitment by government leadership has demonstration or spill-over effects on the citizenry. As a result, borrowers and lenders will be more committed to the terms of loan contracts, thus lowering the incidence of bad loans. Regulatory quality ensures that the government formulates policies and regulations that lower information asymmetry and transaction costs have the effect of reducing hidden actions by lenders and borrowers. This decreases the probability of loan default. Control of corruption is associated with pervasive self-interested behaviour and low levels of honesty, which increase the proportion of 'lemons' in the clientele of the MFIs. This drives up the proportion of bad loans in the loan portfolio. A negative relationship between control of corruption and credit risk is expected.

3.2.2 Empirical Literature

Empirical literature on credit risk in microfinance is scarce but much work has been done using bank-level data. This section reviews microfinance-level studies by comparing their findings to selected bank-level evidence. Studies on drivers of credit risk in microfinance institutions are emerging but are still inconclusive. Most of these studies have focused on credit risk, on one hand, and factors such as group lending methodology (Crabb and Keller, 2006), resilience of microfinance to macroeconomic shocks (Gonzalez, 2007), the gender factor (Schmit and Marrez, 2010; D'espallier et al., 2011), loan size (Chikalipah, 2018) and loan growth (Gonzalez, 2010), on the other hand. Few studies have focused on the determinants of microfinance credit risk (Sainz-Fernandez et al., 2015; Lassoued, 2017).

Group lending schemes have been advocated in microfinance for several reasons. According to Khoi et al. (2013) and Ledgerwood (1999), the application of joint liability provides the peer pressure and social sanctions that act as substitutes for legal enforcement but are effective in enhancing loan repayment and monitoring. Groups also provide an environment for information sharing, which necessarily lowers the "lemons problem" in lending. To test these conjectures, Crabb and Keller (2006) use a large international panel data set of 37 MFIs in Eastern Europe, Africa, Asia and Latin America during 2001-2003 to compare credit risk exposure associated with group-based and individual microloans. They show that risk exposure of MFIs is lower when lending is group-based compared to individual-based lending.

Compared to women, men have better access to financial markets because of their ownership of collateralizable assets like land and houses (Mpuga, 2010). This is the outcome of social constructs and norms which tend to confine women in farm and household activities while men engage in income-generating activities. This unequal access to credit markets forms the motivation of seeking to understand gender differences in the riskiness of microcredit (D'espallier et al., 2011; Schmit and Marrez, 2010). It is also the same motivation that has been used by MFIs to focus on women not only because of their relatively high poverty (Ledgewood, 1999) but also because they are less likely to divert business cash to non-productive uses and they are more likely to prioritize their children's welfare (Kaufman and Riggins, 2010). Using a global dataset of 350 MFIs in 70 countries between 1998 – 2008, D'espallier et al. (2011) test the hypothesis that women are better credit risks compared to men. Evidence shows that lending to women is negatively and significantly correlated with portfolio at risk, loan write-offs and provisions for doubtful debts. Schmit and Marrez (2010) apply a non-parametric bootstrapping technique to compute probability density functions and value-at-risk in 1,144,770 contracts issued at a Maghrebian MFI between 1997 and 2007, which reveal significant male-female similarities and differences in credit risk.

Following overwhelming evidence in the banking industry of the exposure of banks to financial crises, Gonzalez (2007) attempts to establish the resilience of microfinance to macroeconomic shocks. The study investigates the correlation between GNI per capita and different measures of credit risk (portfolio at risk over 30 days, portfolio at risk over 90 days, loan loss rate and write-off ratio) while controlling for other macroeconomic and country-level credit risk predictors. Consistent with Kraus and Walter (2009), the results of Gonzalez (2007) do not suggest any significant exposure of microfinance markets to macroeconomic shocks. This result seems to conflict with bank-level evidence adduced by Salas and Saurina (2002), Louzis et al. (2012), Ashgar and Daly (2010), Vasquez et al. (2012), Das and Ghosh (2007), Castro (2013), Festic et al. (2011), Fofack (2005), Mpofu and Nikolaidou (2018) and many others. These studies are premised on the fact that a recession is associated with lower GDP growth, which lowers the ability of individual and corporate borrowers to service debt and tends to lead to an increase in bad loans. Similarly, a recession is associated with low incomes and low demand for credit. Therefore, credit is extended to low-quality debtors, leading to higher probability of default (Chaibi and Ftiti, 2014).

Predictions of agency theory suggest a positive association between rapid spikes in lending and stability risks. Gonzalez (2007; 2011) and Yimga (2016) fail to confirm this relationship by establishing negative and statistically significant relationships between loan growth and credit risk among MFIs. However, evidence from the banking sector tends to support the predictions of agency theory (Foos et al., 2010; Salas and Saurina, 2002; Das and Ghosh, 2007; Boutriga et al., 2010; Castro, 2013; Festic et al., 2011 and Kauko, 2012). Despite overwhelming evidence of a positive relationship between bank loan growth and credit quality, Clair (1992) finds that loan growth improves credit quality but lowers it after a lag. Generally, these findings show that rapid expansion in credit should not necessarily be associated with deteriorating financial stability but may also be seen as an indicator of deepening financial markets.

It has been hypothesized that giving out small-sized loans significantly affects the likelihood of a crisis in an MFI (Sainz-Fernandez et al., 2015). Chikalipah (2018) pursues this relationship among 632 MFI drawn from 37 countries in SSA. The results suggest that lending to the poor who take smaller loans is less risky compared to the non-poor who access relatively larger loans. Although the study by Chikalipah (2018) is closely related to the current study since it provides evidence on SSA, it is faced with the following shortfalls. First, it examines only micro-level predictors of credit risk but fails to account for the macro-institutional environment despite the fact that earlier studies (Ahlin et al., 2017) and theory (North, 1990; McMullen et al., 2008) have demonstrated the significant role played by these factors in determining microfinance outcomes. Secondly, the study accounts for dynamics but fails to control for time-specific heterogeneity. The use of panel data (which is the basis of most past studies) exposes the findings to both cross-sectional and time-specific heterogeneity, which should be appropriately accounted for during modelling. Apart from Sainz-Fernandez et al. (2015) who controlled for both, the rest of these studies do not explicitly control for time-specific heterogeneity in their panel studies thereby introducing some heterogeneity biases.

Studies by Crabb and Keller (2006), Gonzalez (2007; 2010), Schmit and Marrez (2010), D'espallier et al. (2011) and Chikalipah (2018) have pioneered the understanding of non-performing loans in microfinance. However, they face weaknesses that are attributable to their failure to comprehensively analyse the determinants of credit risk in microfinance. Although they used panel data, the studies failed to account for dynamic factors yet the nature of panel data (combining cross-section and time series) requires the relationships to be modelled as autoregressive processes where past values of a variable affect the current values of that variable. The only exception in this case is Chikalipah (2018) who captures lagged effects of the dependent variable and focuses on SSA. The remaining studies do not provide any evidence on SSA, which has been shown to have relatively higher credit risk levels than other regions.

Recent attempts to comprehensively analyse credit risk predictors in MFIs include Sainz-Fernandez et al. (2015), Yimga (2016), Lassoued (2017) and Noomen and Abbes (2018). Some of the significant drivers of credit risk in MFIs found by Sainz-Fernandez et al. (2015) include excessive liquidity, deposit-asset ratio, loan-employee ratio, profitability, GDP, political stability and private credit bureau. Lassoued (2017) finds that group lending, share of loans advanced to women, income diversification, private and public bureaus and low enforcement costs significantly influence credit risk.

Noomen and Abbes (2018) provide evidence on a unique segment of microfinance – Islamic MFIs. The study confirms that credit risk among these MFIs is influenced by the number of active borrowers, loan loss provision, the return on gross loan portfolio, risk coverage, return on assets, inflation, the size and age of MFIs. Studies on Islamic finance are premised on the fact that unlike traditional banking, Islamic finance is unique in terms of cost efficiency (Samad and Hassan1999), default rates (Baele et al., 2010; Abedifar et al., 2013), insolvency risk (Cihak and Hesse, 2010) and market power[14]. This is attributed to principles governing financial transactions in Islamic banks, which forbid the payment or receipt of interest and the use of many derivative products (Abedifar et al. 2013). However, other studies have established no significant difference between traditional banks and Islamic banks in terms of production technology (El-Gamal and Inanoglu, 2005), cost and profit efficiency (Majid and Rais, 2003; Mohamad et al., 2008; Bader et al., 2008).

The main weakness of the studies by Sainz-Fernandez et al. (2015), Lassoued (2017) and Noomen and Abbes (2018) is that they ignore credit risk dynamics and fail to provide any specific evidence on SSA. Yimga (2016) accounts for credit risk dynamics but fails to control for institutional factors and does not provide any evidence on SSA. Chikalipah (2018) estimates the relationship between loan sizes and credit risk in SSA but fails to account for the macro-institutional environment despite the fact that earlier studies (Ahlin et al., 2017) and theory (North, 1990; McMullen et al., 2008) have demonstrated the significant role played by these

[14] Abedifar et al. (2013).

factors in determining the performance of microfinance. Apart from Yimga (2016) and Chikalipah (2018), previous studies did not account for the dynamic effects of credit risk, yet time series econometrics requires economic relationships to be modelled as autoregressive processes where past values of a variable affect the current values of that variable. They apply mainly random effects or fixed effects estimators, which may be limited to deal with endogeneity issues in the data. Again, it should be noted that panel data (which is the basis of most past studies) is affected by both cross-sectional and time-specific heterogeneity, which should be appropriately accounted for during modelling. Apart from Sainz-Fernandez et al. (2015) who controlled for both, the rest of these studies do not explicitly control for time-specific heterogeneity in their panel studies.

Some of the bank-level macroeconomic factors that have been included in credit risk regressions include CPI, GDP, current account, gross fixed capital formation, consumption, FDI, trade balance, unemployment, external debt, money supply, interest rate and stock market index. Bank specific factors include total loans, leverage ratio, liquidity and interest on loans. However, a few studies have also incorporated institutional factors in their models. For instance, Breuer (2006) includes legal institutions (e.g. lack of property rights, law and order, legal origin), social institutions (e.g. ethnicity, corruption, income equality), political institutions (e.g. voice, government stability) and banking institutions (bank industry concentration, government ownership of banks, restricted activity in securities market, guidelines for asset diversification).

Generally, the following gaps in knowledge have been identified. Analyses of credit risk determinants in finance are few and evidence is only emerging. Past MFI level analyses did not go beyond global results to make international comparisons at the regional levels. Only few of the previous studies controlled for the dynamics of credit risk. This study contributes to the microfinance literature by not only documenting determinants of credit risk in SSA but also predictors of credit risk in SA, LAC, EECA and EAP. The study uses a two-way error components model and employs dynamic system GMM estimators which have been recommended for dealing with endogeneity problems (Roodman, 2009). In addition, the study tests the effect of non-linearities in the relationship between credit risk and loan growth, which has not been analysed in previous micro-finance literature except by Gonzalez (2010).

3.3 Methodology

3.3.1 Model Specification

Since the objective of this study is to determine dynamic effects as well as to identify the determinants of credit risk, the model employed follows Foos et al. (2010), Salas and Saurina (2002), Louzis et al (2012), Das and Gosh (2007) and Castro (2013) to specify a one-way error components model.

$$r_{it} = \beta_1 r_{i,t-1} + \boldsymbol{M}'_{it}\theta + \boldsymbol{X}'_t\rho + \mu_i + v_{it} \qquad (5)$$

The dependent variable r_{it} is credit risk. Vector $\boldsymbol{M}$ contains micro-level variables, which include loan growth, provision for loan impairment, capital asset ratio and return on equity. The macro-institutional variables, which are contained in vector $\boldsymbol{X}$, capture country-level macroeconomic and institutional factors. These factors include GDP growth, inflation, private credit, political stability and the ease of getting credit. μ_i captures MFI-specific heterogeneity while v_{it} is the idiosyncratic error term.

Panel data is characterised by several heterogeneities. For instance, the data used for this study is exposed to MFI-specific heterogeneity as well as time-specific heterogeneity. In view of this, equation (5) can be modified by incorporating a variable that captures time-specific effects (γ_t). As such, the equation becomes:

$$r_{it} = \beta_1 r_{i,t-1} + \boldsymbol{M}'_{it}\theta + \boldsymbol{X}'_t\rho + \mu_i + \gamma_t + v_{it} \qquad (6)$$

Applying ordinary least squares estimators to equation (6) results in the following econometric problems. First, there is reverse causality between credit growth and risk. Therefore, credit growth is endogenous because of this reverse causality. This problem leads to biased estimates because credit growth will be correlated with the error term. Second, time-invariant MFI-specific effects will be correlated with other explanatory variables. Third, the presence of a lagged variable ($r_{i,t-1}$) gives rise to autocorrelation.

Although fixed effects instrumental variable estimators can be applied to deal with the first and second problems, they will not be able to deal with the autocorrelation problem. This issue can be resolved by using a GMM approach. This study adopts the two-step system GMM estimator devised by Arellano and Bover (1995) and Blundell and Bond (1998) because it is more precise especially when using finite samples. The estimator is based on a system comprising a first differenced model and a levels equation. The first differenced equation uses lagged level variables as instruments whereas the levels equation uses lagged first differences as instruments.

3.3.2 Data Type and Sources

The data that is used in this study is drawn from an MFI-level database, which is compiled by the Microfinance Information eXchange, Inc (or the MIX database). The MIX data was merged with country-level data from the World Development Indicators (World Bank) spanning 2000-2014, Doing Business Indicators (World Bank) spanning 2004-2014 and World Governance Indicators (World Bank) spanning 2000-2014. The MIX database runs from 1996 to 2014 and contains about 16,634 observations with 23% coming from SSA, 16% from SA, 27% from LAC, 18% from EECA, 12% from EAP and 4% from MENA. Notably, the MIX database is unbalanced in that the number of MFIs covered and the number of observations fluctuates from year to year. In 1996, there were 30 MFIs in the global database. This number rises to 1,199 in 2005, 1,589 in 2011 and 958 in 2014. Globally, the median number of MFIs in the sample over 2006-2014 is 958. The data covers 121 countries. It is estimated that 37 MFIs are from SSA, 16 are from EAP, 24 are from EECA, 26 are from LAC, 10 are from MENA and seven are from SA.

3.3.3 Definition and Measurement of Variables

Credit risk is the sum of portfolio at risk and write-off ratio (Wagner and Winkler, 2013; Gonzalez, 2010; Sinkey and Greenwalt, 1991). Portfolio at risk refers to the ratio between loans that are overdue by more than 30 days and total loans. Write-off ratio is the portion of loan portfolio that has been declared unrecoverable and therefore posted as a loss (D'espallier et al., 2011).

Provision for loan impairment is the provision for loan losses as a percentage of total assets. MFIs account for customers' loan defaults by keeping reserve accounts against which such losses are charged (Foos et al., 2010; Bouvatier and Lepetit, 2008; Noomen and Abbas, 2018). Therefore, it is expected that provision for loan impairment will be negatively associated with *credit risk.*

Loan growth is the log difference in year-end gross loan portfolio. It is used as a proxy for excessive risk-taking (Gonzalez, 2007; 2010; Laidroo and Mannassoo, 2014; Vithessonthi, 2016). Overall, the effect of *loan growth* on *credit risk* is ambiguous depending on whether *loan growth* is triggered by supply or demand shifts (Keeton, 1999).

Capital asset ratio is the share of equity capital in total assets of the MFI. Agency theory stipulates that well capitalised MFIs will tend to be more conservative in lending because this lowers their risk exposure (Jensen and Meckling, 1976; Shleifer and Vishny, 1989; Baker and Wurgler, 2002). It is expected that the capital-asset ratio will be negatively correlated with *credit risk*.

Return on equity measures the earnings after taxes divided by total equity. According to Chaibi and Ftiti (2015), Love and Ariss (2014), Abid et al. (2013) and Vithessonthi (2016), it is a proxy for management quality. Higher profitability indicates better management quality but it could also signal the existence of soft budget constraints and excess cash flows leading to careless lending behaviour by MFIs. There is an ambiguous relationship between profitability and *credit risk*.

GDP per capita growth is the percentage growth in real GDP per capita. Measured as the annual % change in real GDP per capita, it is included to capture business cycle effects. It is expected that there is procyclicality between *GDP per capita growth* and *loan growth* (Hofmann, 2004).

Private credit refers to the domestic credit given to the private sector by banks as a share of GDP. It is an indicator of financial sector development and can also be used as a measure of indebtedness of firms and households (Pesolla, 2011; Castro, 2013). Therefore, the relationship between *private credit* and *credit risk* is ambiguous.

Inflation is the annual percentage change in the consumer price index. High *inflation* is usually a source of macroeconomic risk and uncertainty. The effect of *inflation* on *credit risk* is ambiguous. The negative effect works through two channels. The first channel is based on the Phillips curve hypothesis, which postulates a trade-off between *inflation* and unemployment (Mishkin, 2013). The second channel works through the effect of *inflation* on the real value of the loan. The real value of the loan tends to fall when *inflation* is high thus reducing the probability of default.

Political stability measures the likelihood of political unrest or politically-motivated violence (Indicators, 2015). The variable is a perception index ranging from -2.5 (weak performance) to 2.5 (strong performance) as reported in the World Governance Indicators of the World Bank.

Ease of getting credit measures "the legal rights of borrowers and lenders with respect to secured transactions and the reporting of credit information" (Business, 2017). It is measured in terms of distance to the frontier on a scale from 0 to 100. The maximum value of 100 is the frontier or best practice. This measure captures the gap between an economy's performance and the best practice value among the entire sample. The variable is drawn from the World Bank's Doing Business Indicators database.

3.4 Empirical Results

3.4.1 Descriptive Statistics

Mean credit risk was 12% in SSA over the 2004-2014 period[15]. Results in Appendix Table A7 indicate that most of the variables are not normally distributed since their skewness and kurtosis values are at variance with the conventional skewness of 0 and kurtosis of 3 for a normal distribution. The skewness and kurtosis values for credit risk are 4.99 and 45.24 respectively, implying that the distribution is positively skewed with very thin tails. That means the error term in equation (6) is also likely to be non-normal. This problem is exacerbated by the presence of outliers in the database. To deal with this problem, the data was truncated at the 5% percentile in the upper and lower tails of the distribution. Similarly, GMM estimators were

[15] It is important to note that the median credit risk is significantly higher in SSA (7.1%) compared to non-SSA (4.5%). Huge differences between the SSA mean and median is because of the presence of outliers, which have a bigger effect on the mean.

deployed to allow reliable estimation of the parameters when the distribution of the error term is not normal.

Mean test results reported in Table 4 show that there are significant differences between loan growth, private credit, GDP per capita growth, inflation, political stability and the ease of getting credit in SSA and non-SSA. This gives enough reason to believe that MFIs in SSA operate under different macro-institutional conditions compared to MFIs elsewhere. For example, the share of credit by the banks to the private sector in GDP for SSA is 17.5% compared to 33.7% for non-SSA. This implies that MFIs in SSA operate in markets with very low financial depth compared to their counterparts elsewhere. Similarly, MFIs in SSA operate in an environment characterised by high macroeconomic uncertainty as measured by higher inflation levels (see Table 4).

Table 4: Comparisons of means – SSA and non-SSA

	Non-SSA	SSA	difference	t-ratio
Credit risk (ratio)	0.31	0.12	0.192	(0.51)
Loan growth (Ratio)	0.264	0.29	-0.026*	(-2.14)
Provision for loan impairment (ratio)	0.018	0.02	-0.002	(-1.85)
Capital asset ratio	0.354	0.32	0.034	(1.32)
Return on equity (ratio)	0.146	-0.09	0.236	(0.32)
Private credit (%)	33.71	17.48	16.23***	(50.43)
GDP per capita growth (%)	4.561	2.59	1.97***	(25.40)
Inflation (%)	4.964	7.79	-2.83***	(-9.73)
Political stability (index)	-0.753	-0.54	-0.213***	(-14.92)
Ease of getting credit (index)	43.62	33.11	10.5***	(24.04)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.2 Regression Results

The correlation matrix reported in Appendix Table A8 indicates that there is low correlation among most of the variables. The only exception is the high correlation of 0.7 between loan growth and loan growth squared, which is expected.

Before running the regressions, some of the variables are transformed. These include credit risk which is log-transformed and the governance indicators which are transformed by computing their percentage growth. After running the regressions, the results are checked for proper specification by conducting the Arellano-Bond test for zero autocorrelation in first differenced errors, the F-test for joint significance of the coefficients as well as the Hansen test for overidentifying restrictions (H_0 = overidentifying restrictions are valid). The Arellano-Bond test is designed to test for zero autocorrelation (H_0 = no autocorrelation). Usually, AR (1) is expected to reject the null while AR (2) should fail to reject the null. The Arellano-Bond test reveals that all the regression results reported in sections 3.4.2.1 and 3.4.2.2 passed the autocorrelation test for the first and second lag. The Hansen test confirms that the overidentifying restrictions are valid.

3.4.2.1 Determinants of Credit Risk in SSA

Table 5 reports the regression results of the baseline model using the two-step system GMM estimator. For comparison purposes and in order to establish robustness, results for alternative specifications using fixed effects, random effects and OLS estimators are presented in Appendix Table A9. The results in Table 5 show that the main predictors of credit risk in SSA are lagged credit risk, loan growth, provision for loan impairment, GDP per capita growth and ease of getting credit. In addition, the study finds that the effect of loan growth on credit risk is non-linear and robust to different estimators. Credit risk falls with loan growth until a trough at 36.8% when this relationship is reversed. Therefore, this study confirms that loan growth becomes risky beyond 36.8%. Below a loan growth of this level, MFIs pursuing an aggressive lending policy face much less credit risk exposure. This result could be explained by either demand shifts or productivity shifts but not supply shifts (Keeton, 1999), in which case loan growth could be seen as an equilibrium convergence process (Kiss et al., 2006). This is consistent with Gonzalez (2007; 2010) and Yimga (2016) who find a significantly negative relationship between MFI loan growth and portfolio at risk. Clair (1992) also finds that bank loan growth improves loan quality. However, these past studies did not test for non-linearity in the relationship between credit risk and loan growth, which is found by the current study to be important.

There is evidence that dynamics matter for credit risk. The first lag of credit risk is significantly positive with an elasticity of 0.22, which implies that there exists conditional convergence in credit risk (Fung, 2009; Asongu, 2013; Asongu and Nwachukwu, 2016). This result is robust to different specifications although the magnitudes vary by type of estimator. Ideally, this result can be interpreted in several ways. First, the result shows that an increase in lagged credit risk by 1% increases the current credit risk by 0.22%. Secondly, it means credit risk was higher among MFIs that were already facing high risk exposure. This result may reflect the fact that

MFI managers are backward-looking when it comes to credit risk assessment. They keep non-performing loans in their books for longer periods of time.

Table 5: Credit risk determinants in SSA: Baseline results

	Credit risk
Credit risk (L1)	**0.22****
	(0.097)
Loan growth	**-0.89***
	(0.459)
Loan growth squared	**1.21****
	(0.556)
Provision for loan impairment (in logs)	**0.18*****
	(0.042)
Capital asset ratio	0.09
	(0.251)
Return on equity	-0.06
	(0.078)
Private credit	-0.00
	(0.005)
GDP per capita growth	**-0.02***
	(0.012)
Inflation	-0.00
	(0.007)
Political stability	-0.02
	(0.013)
Ease of getting credit	**0.62*****
	(0.139)
No of observations	394
No of MFIs	149
No of instruments	56
F-stat	4.84
AR (1) [p-value]	0.021
AR (2) [p-value]	0.812
Hansen [p-value]	0.165

The dependent variable is credit risk (in logs). Endogenous variables are lagged credit risk, loan growth and loan growth squared; the rest of the variables are treated as exogenous. Two step system GMM estimator, robust standard errors (in parentheses), small-sample adjustments and orthogonal deviation were applied. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Results for Arellano-Bond test for zero autocorrelation in first differenced errors (H_0=there is no autocorrelation) and F-test for joint significance of parameters are reported. Results of Hansen test for overidentifying restrictions (H_0=overidentifying restrictions are valid) are also reported. (L1) indicates the first lag.

Against expectations, provision for loan impairment positively and significantly predicts credit risk. When provision for loan impairment increases by one unit, credit risk increases by 18%. Higher provisions for loan defaults are made when risk exposure is high. This result is consistent with Bouvatier and Lepetit (2008) and Boudriga et al. (2010) who found that the relationship between non-performing loans and provisioning for doubtful loans in banks was significantly positive. However, in terms of prudential regulation, this result is worrying because regulators usually encourage loan loss provisioning in order to lower risk exposure.

There is evidence that business cycles significantly affect loan defaults in MFIs. Credit risk falls by 2% for each percentage point increase in GDP per capita growth. This is explained by the fact that GDP growth per capita growth is associated with optimistic customer expectations, which spurs borrowing by economic agents (firms and households). The agents increase their indebtedness because of the improvement in their loan servicing capacity during an economic expansion. However, this result is inconsistent with Ahlin et al., (2011) who found that GDP growth had no significant effect on portfolio at risk.

As expected, the ease of getting credit is significantly associated with higher credit risk. Credit risk increases by 62% for each unit increase in the ease of getting credit. When there is easy credit, financial exposure to problems of moral hazard and adverse selection is increased with the result that the portfolio of non-performing loans goes up. Easy credit may mean aggressive lending by MFIs is driven by supply shifts rather than demand or productivity shifts (Keeton, 1999), which results in a disequilibrium (excess supply of loans) and high indebtedness. These conditions result in a high probability of default.

3.4.2.2 A Comparative Analysis of Credit Risk Determinants

In this section, baseline regression results for SSA are compared to regression results for four regions (EAP, EECA, LAC, SA) and two groupings (non-SSA and World). Table 6 reproduces the results for SSA and juxtaposes them against results for EAP, EECA, LAC, SA, non-SSA and the World.

Table 6 shows that the coefficients on lagged credit risk are positive and statistically significant in all regressions, implying that dynamics matter for credit risk in MFIs. However, credit risk is most persistent in EAP where a permanent increase in lagged credit risk by 1% increases the expected value of current credit risk by 0.43%. Credit risk is least persistent in SSA where a 1% rise in lagged credit risk is associated with a 0.22% increase in current credit risk. In SA, LAC and EECA, 1% increase in lagged credit risk is, respectively, significantly correlated to 0.4%. 0.33% and 0.32% rise in current credit risk.

The following additional observations can be made from Table 6. Firstly, loan growth has a non-linear relationship with credit risk in SSA, EAP and LAC but not in EECA and SA. The turning points in SSA, EAP and LAC are 36.7%, 363% and 108%, respectively. This implies that MFIs in SSA reach their turning point faster than those in EAP and LAC. This result confirms the argument that fast loan growth rates that were experienced in SSA during 2000-2007 averaging 39.9% were responsible for the financial instability that was witnessed in the sector in subsequent years (Riquet and Poursat, 2013; Boateng et al., 2006). However, it is probable that the crises that were experienced in other regions may have had little linkages with fast loan growth.

Table 6: Credit risk determinants – SSA vs non-SSA

	Dependent variable: credit risk (in logs)						
	SSA	EAP	EECA	LAC	SA	Non-SSA	World
Credit risk (L1)	**0.22****	**0.49*****	**0.32*****	**0.33*****	**0.40*****	**0.34*****	**0.47****
	(0.097)	(0.085)	(0.094)	(0.065)	(0.060)	(0.067)	(0.189)
Loan growth	**-0.89***	**-0.80*****	**-1.48*****	**-1.17*****	**-0.65*****	**-0.50*****	**-2.15*****
	(0.459)	(0.259)	(0.489)	(0.342)	(0.131)	(0.170)	(0.419)
Loan growth squared	**1.21****	**0.11*****	0.45	**0.54****	**-0.27****	**0.06****	**0.30*****
	(0.556)	(0.034)	(0.415)	(0.249)	(0.117)	(0.027)	(0.068)
Provision for loan impairment (in logs)	**0.18*****	**0.27*****	**0.24*****	**0.22*****	**0.26*****	**0.30*****	**0.21*****
	(0.042)	(0.057)	(0.055)	(0.024)	(0.037)	(0.026)	(0.048)
Capital asset ratio	0.09	**-0.27***	-0.02	0.12	-0.01	0.04	-0.06
	(0.251)	(0.160)	(0.220)	(0.080)	(0.151)	(0.074)	(0.089)
Return on equity	-0.06	-0.09	-0.35	**-0.03*****	**-0.01*****	**-0.02****	**-0.01*****
	(0.078)	(0.112)	(0.267)	(0.006)	(0.004)	(0.007)	(0.004)
Private credit	-0.00	**-0.01****	0.00	-0.00	**-0.02*****	-0.00	**-0.00***
	(0.005)	(0.005)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
GDP per capita growth	**-0.02***	-0.03	**-0.02****	**-0.01****	0.02	**-0.02*****	-0.00
	(0.012)	(0.042)	(0.008)	(0.006)	(0.012)	(0.005)	(0.007)
Inflation	-0.00	**0.07*****	-0.01	-0.00	**0.02****	**-0.01*****	-0.00
	(0.007)	(0.023)	(0.010)	(0.006)	(0.008)	(0.004)	(0.006)
Political stability	-0.02	0.29	**0.04*****	0.01	-0.09	**0.03*****	0.01
	(0.013)	(0.220)	(0.012)	(0.014)	(0.343)	(0.010)	(0.014)
Ease of getting credit	**0.62*****	**-0.86***	0.01	**0.22*****	0.05	-0.03	-0.05
	(0.139)	(0.438)	(0.138)	(0.081)	(0.048)	(0.058)	(0.065)
No of observations	394	329	408	1,305	715	2,853	3,257
No of MFIs	149	118	110	294	217	763	913
No of instruments	73	89	73	57	89	105	69
F-Stat	123.6	151.6	342	856.5	227.2	32.8	40.1
AR (1) [p-value]	0,031	0.002	0.000	0.000	0.002	0.000	0.000
AR (2) [p-value]	0.920	0.867	0.940	0.728	0.748	0.493	0.115
Hansen (p-value)	0.128	0.113	0.225	0.533	0.15	0.106	0.530

The dependent variable is credit risk (in logs). Endogenous variables are lagged credit risk, loan growth and loan growth squared; the rest of the variables are treated as exogenous. Two step system GMM estimators, robust standard errors (in parentheses), small-sample adjustments and orthogonal deviation were applied. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Results for Arellano-Bond test for zero autocorrelation in first differenced errors (H_0=there is no autocorrelation) and F-test for joint significance of parameters are reported. Results of Hansen test for overidentifying restrictions (H_0=overidentifying restrictions are valid) are also reported. (L1) indicates the first lag. All regressions include time and type dummies. A constant is included in the regressions but not reported. Results for MENA are excluded due to few observations.

The second observation is that provision for loan impairment is robust and significantly correlated with credit risk in all regions. However, the magnitude of this effect varies across regions. This implies that MFIs do not generally use provision for loan losses as a mechanism to cushion them against potential loan losses. If this were the case, the sign on the coefficient on provision for loan impairment would be reversed.

Third, the results show that the macroeconomic environment is important in explaining credit risk in all regions. Growth in GDP per capita is associated with lower credit risk in SSA, EECA and LAC while inflation increases credit risk in EAP and SA. Domestic credit to the private sector reduces credit risk in EAP and SA. These findings suggest that GDP per capita growth in SSA, EECA and LAC is associated with increased capacity to service debt and lower demand for credit resulting in low probability of loan defaults. However, increasing domestic credit to the private sector leads to lower credit risk because of lower informational constraints (absence, uncertainty and asymmetry) that accompany deepening of the financial sector in EAP and SA. Inflation is found to positively and significantly influence credit risk in EAP and SA because an increase the consumer price level is an indicator of macroeconomic uncertainty. When inflation is high, the plans are usually disrupted and actions of borrowers cannot be known in advance. When this is the case, exposure to information asymmetry goes up.

Finally, institutional factors significantly affect the level of credit risk. Whereas the ease of getting credit is a predictor of credit risk in SSA, EAP and LAC, political stability significantly affects the level of risk in EECA. Notably, the coefficients on ease of getting credit in SSA and LAC are positive and significant while the coefficient on the same variable in EAP is negative and significant. Therefore, the ease of getting credit in SSA and LAC seems to be accompanied by informational problems of moral hazard and adverse selection whereas in EAP, ease of getting credit may be accompanied by more effective screening of loan applicants, monitoring the loans and assessing the collateral.

The coefficient on political stability is positive and statistically significant in EECA. This result can be attributed to the certainty in decision making which happens when rules and regulations can be predicted in advance. This may push potential entrepreneurs out of the formal economy into the informal economy. Increased entry into microenterprise spurs the demand for micro loans, which leads to accumulation of non-performing loans.

3.5 Conclusion and Policy Recommendations

The purpose of this study is to identify determinants of credit risk in SSA MFIs and to establish whether these determinants have the same effects on credit risk in other regions of the world. To investigate these conditions, GMM estimators were applied in regression models for SSA as well as SA, LAC, EECA and ECA. Data from four different databases (MIX market, World Development Indicators, World Governance Indicators and the Doing Business Indicators) was used in the regressions. The findings suggest that the main predictors of credit risk in SSA are lagged credit risk, loan growth, provision for loan impairment, growth in GDP per capita and ease of getting credit. In addition, the study finds that the effect of loan growth on credit risk is non-linear; credit risk falls with loan growth until a trough at 36.8% when this relationship is reversed. At the global level, credit risk is determined by lagged credit risk, loan growth, provision for loan impairment, return on equity and credit to the private sector by banks.

Although lagged credit risk, loan growth and provision for loan impairment significantly affect credit risk in all regions, it is found that the drivers of credit risk in SSA are not necessarily the same factors that drive credit risk in other regions. For instance, GDP per capita growth significantly affects credit risk in SSA, EECA and LAC whereas inflation has a notable impact on credit risk in EAP and SA.

In terms of policy, regulators of MFIs should be concerned that loan loss provisioning is positively and significantly associated with credit risk. Regulators usually recommend loan loss provisioning as a measure to lower credit risk exposure. However, the results suggest that this prudential tool may not be achieving the desired results. There is need to explore further the effect of loan loss provisioning in regulated MFIs.

Since the effect of loan growth is non-linear, MFIs should be encouraged to enhance their outreach but keep an eye on the quality of their credit. They should be able to determine the turning point of their outreach activities so that they know at what level their lending becomes risky. The results also suggest that credit risk scoring, which is the dominant approach that MFIs apply in loan screening, should consider past levels of risk as this is a predictor of future credit risk outcomes.

MFIs should be encouraged to hire qualified personnel because this tends to improve profitability. Since loan growth is negatively related to credit risk, MFIs should be encouraged to continue to improve the quality of their loan portfolio through devoting enough resources for credit administration and loan monitoring. This approach not only strengthens credit underwriting standards, it also diversifies their loan portfolio along sectors and regions.

Similarly, government agencies, Central Banks and ministries of finance, that manage growth policy should prudently manage the reforms that enhance the earning capacity of firms and households. They should provide incentives for entrepreneurship, savings and capital. Higher incomes in the economy are associated with lower credit risk. Similarly, institutional reforms that enhance access to credit are good for income generation and the growth of small businesses, although this may enhance credit risk exposure. The role of credit bureaus and other interventions that lower information asymmetry should be encouraged. Moreover, these findings suggest that MFIs in reforming countries need to develop new customer-focused approaches of increasing lending such that the institutional reforms do not have a negative impact on the quality of their loan portfolio.

Chapter 4

Factors Influencing Households' Access to MFI Credit in Kenya

4.1 Introduction

Understanding why many people, especially the poor, remain excluded from credit markets remains a global scholarly and policy concern. In response, a large body of literature has grown over the years seeking to explain why access to credit differs so much across households, individuals and even countries. Extant literature has brought to the fore some key insights, which have had a bearing on knowledge and policy.

Firstly, it has been established that both individual characteristics (such as age, gender, education, employment status, income and so on) and household characteristics (such as family size, consumption, assets, poverty status, etc.) are significantly associated with the use of credit (Mohieldin and Wright, 2000; Okurut, 2006; Manrique and Ojah, 2004; Zeller, 1994). These findings have been used to prescribe welfare policies that enhance the human capital endowment and productivity of individuals and households as a way of making them creditworthy (Okurut et al., 2005). Secondly, it is evident that in some cases formal and informal sectors are symbiotic rather than dualistic (Khoi et al., 2013; Mohieldin and Wright, 2000; Kochar, 1997). These findings have an implication that the informal sector needs to be harnessed, rather than eliminated as was earlier emphasized by market failure proponents of public policy. In fact, it may hold the promise for the efficient functioning of the formal sector. Thirdly, institutional factors such as race, ethnicity, trust, property rights, as well as law and order determine outcomes in the credit markets (Okurut, 2006; Khoi et al., 2013; Farazi, 2014;

Turvey and Kong, 2010; Crook, 2001; Akoten et al., 2006). Given that the effect of institutional factors has a long gestation period, lowering institutional barriers may require systematic and gradual measures. Since households are often exposed to shocks, the fourth element to consider is the fact that credit has been used for consumption-smoothing, and to cushion households from shocks, rather than for investment (Bending et al., 2009; Zeller, 1994; Diagne, 1999). These findings highlight the understanding that the demand for credit extends beyond meeting investment demands, and points to other social demands that may require new credit scoring approaches.

With a lack of data on mobile financial services (MFS)[16] since such technologies are relatively new in many countries, relatively few scholarly works have analysed the impact of mobile financial services on access to credit. But Kenya's dynamic market for MFS is almost mature; there is heightened scholarly interest in this area and data is becoming available. Therefore, the current study attempts to fill this gap in knowledge by providing evidence on the impact of M-banking, M-money and M-credit on the access to MFI credit in Kenya. MFS can be used to explain why access to credit differs across individuals and households. This is justified by transaction cost and distance theories (Weber et al., 2012). Unlike traditional credit, M-credit platforms are fast, automated and remote, which allows them to dismantle the collateral, distance and transaction cost barriers (Aker and Mbiti, 2010; Kaufman and Riggins, 2010).

[16] In this study, mobile financial services refer to M-money, M-banking and M-credit. M-Money allows users to exchange cash for an "e-float" on their phones, to send e-float to other cellular phone users and to exchange e-float back to cash (Mbiti and Weil, 2011). M-banking refers to the provision of banking services (checking account balances, transfer funds, obtain customised information, pay for goods and services and so on) with the help of a mobile phone (Donner and Tellez, 2008). M-credit was launched in Kenya in 2012 but there are currently 20 digital credit providers. The M-credit platform executes loan application, credit scoring, approval and disbursement remotely without the need to physically visit the credit granting organization.

The current study applies a discrete choice framework using 2013 (N=6449) and 2015 (N=8665) household data. The data was collected under the Financial Access Partnership comprising the Central Bank of Kenya, Kenya National Bureau of Statistics and Financial Sector Deepening Trust. Due to the fact that access to credit and income are jointly determined, the study employed instrumental variable estimators to forestall endogeneity concerns. Tests for validity of the instruments and endogeneity of income justified the use of IV Probit and IV 2SLS. The results show that the factors influencing the probability of using MFI credit in Kenya are not similar over the two periods analysed (2013 and 2015). There are also variations in the results when analysed by poverty status. In 2013, the predictors of the propensity to use MFI credit are income, gender and type of cluster. M-money plays a complementary role in accessing MFI credit among the non-poor. In 2015, those using M-banking and M-credit are less likely to use MFI credit. In addition, young, male, married, uneducated and urban-based demographics as well as people with lower incomes and residents of small-sized households are less likely to use MFI credit. Two general findings stand out. First: increasing log income by one unit increases the probability of using MFI credit by 23%. This finding implies that MFIs are lending more to the non-poor, which is not their target group. Therefore, borrowing by the non-poor from MFIs is dislodging the poor from accessing MFI credit. The second finding is that M-banking and M-credit are significantly and negatively associated with the probability to use MFI credit, indicating that these mobile-based services are drawing users away from MFI credit. This goes against the expectation that these financial innovations aim to bank the poor.

The investigation of MFS impact on the microfinance sector continues as follows. Section 4.2 discusses the layering of the credit market in Kenya. Section 4.3 reviews the literature, identifying the aspects of microfinance credit and MFS requiring more scholarly attention.

Section 4.4 provides the methodology employed in this study while Section 4.5 reports the regression results and discusses the findings. Finally, the paper provides some policy recommendations in Section 4.6.

4.2 Structure of the Credit Market in Kenya

Households and firms in Kenya obtain their credit from formal, semi-formal and informal sources. The formal sector consists of private and public banks. In 2015, there were 43 commercial banks and nine microfinance banks operating in the country – all licensed, regulated and supervised by the Central Bank of Kenya. The main objective of commercial banks is to generate profit by providing relatively large individual and enterprise loans as well as by mobilizing savings from the public. Private banks are mainly concentrated in urban centres but public banks have extended their services beyond urban areas into rural areas. For political and economic reasons, public banks have been used by the government to achieve public policy goals. For example, they are often used to channel credit to strategic sectors such as agriculture, the youth, women and university students among others. Like many commercial banks elsewhere, access to banks in Kenya is limited by (a) minimum balance requirements to open an account; (b) collateral requirements; and (c) bureaucratic processes. In 2007, only 4% of the Kenyan population had accessed a bank loan (GOK, 2007). This proportion had grown to 6.5% and 7.3% in 2013 and 2015, respectively (see Table 7). This shows that bank penetration has been increasing although access has been relatively low among the poor – estimated at 2.7% in 2015 (see Table 7).

Table 7: Sources of Credit in Kenya

	2015 (%)			2013 (%)		
Source of loan	Poor	Non-poor	All	Poor	Non-poor	All
N	3549	5116	8665	1958	4222	6190
Bank	2.7	10.5	7.3	1.7	8.9	6.5
MFI	4.8	15.6	15.5	3.8	12.8	9.8
Government	1.0	3.2	2.3	0.5	1.5	1.2
Employer	1.8	4.1	3.2	1.8	4.3	3.5
ASCA	6.4	10.4	8.8	1.4	3.6	2.8
Chama	5.8	7.1	6.5	6.3	10.4	8.9
Family & friends	18.0	23.4	21.2	13.9	19.7	17.5
Shylock	1.1	2.3	1.8	2.0	2.9	2.6
Shopkeeper	14.1	8.7	10.9	10.3	14.7	12.9
Buyer	1.2	1.4	1.3	1.8	3.9	3.2
Mortgage	1.1	3.4	1.7	0.6	2.2	1.6
Hire purchase	0.7	1.2	1.0	-	-	-
Supplier	22.1	24.6	23.5	-	-	-
Digital	2.9	15.2	10.1	-	-	-
All	**48.9**	**62.4**	**56.9**	**28.5**	**46.1**	**39.8**

Source: Computed by author using 2013 and 2015 FinAccess data. Banks consist of commercial banks, Postbank and microbanks. Government refers to Joint Loans scheme, Higher Education Loans Board, Youth Fund; MFI refers to microfinance institution and combines credit-only MFIs and SACCOs; ASCA refers to Accumulating Savings and Credit Association; *Chama* refers to self-help groups; shylock refers to informal money lender; digital credit refers to M-Shwari, Kenya Commercial Bank (KCB) MPESA and others.

Non-governmental Organizations (NGOs), Savings and Credit Co-operative Associations (SACCOs) and Government loan programmes (including Joint Loans Scheme, Higher Education Loans Board, Youth Fund, Women Fund and others) fall under the semi-formal strand. Unlike formal institutions, NGOs and SACCOs are not licensed and regulated by the Central Bank of Kenya. Instead, they are licensed and supervised by Sacco Societies Regulatory Authority and the NGO Co-ordination Board. SACCOs have a welfare focus with deposit mobilization as an overriding strategy while NGOs depend more on donor and government support, which comes via technical assistance and subsidies (Ledgerwood, 1999). Generally, semi-formal institutions integrate the features of both formal and informal sector players. Due to their poverty focus, NGOs in Kenya have been at the forefront of introducing the group approach[17], which is an internationally tested approach (Bendig et al., 2009). In 2015, Kenya had 3816 SACCOs and 21 credit-only MFIs. Although MFIs have a poverty focus, they seem to serve more non-poor people compared to the poor. This fact is evident in both 2013 and 2015 (see Table 7). In 2015, 4.8% of the poor received credit from MFIs compared to 15.6% of the non-poor. However, the importance of MFIs in Kenya's credit market increased between 2013 (9.8%) and 2015 (15.5%).

Credit-only NGOs can be traced to the establishment of Kenya Rural Enterprise Programme under USAID sponsorship in the 1980s (Johnson and Nino-Zarazua, 2009) as well as the establishment of Kenya Women Trust and Faulu Kenya. According to the Annual Report on the Microfinance Sector in Kenya, the total assets of the microfinance sector in 2013 amounted to about Ksh 315.7 billion, the loan portfolio was Ksh 63.1 billion and outreach of the sector was 808,399 persons (AMFI, 2014). The microfinance sector is dominated by microfinance banks (which hold 45% of the loan portfolio) and women (who constitute roughly 62% of the active borrowers).

Proponents of the credit rationing school view the evolution of the informal lending sector as a consequence of failure in credit markets. Consistent with this view, the sector has been left to operate on the fringes of government regulation and supervision (Ledgerwood, 1999). Despite this exclusion, the informal credit sector in Kenya remains huge, resilient and growing. As shown in Table 7, the informal sector consists of employers, ASCAs, *chamas* (self-help groups), friends and relatives, shylocks, shopkeepers, buyers and suppliers. In 2013, out of all Kenyan adults who had borrowed money, about 48.2% of the credit was sourced from the informal sector. This proportion rose to 77.2% in 2015. Although not universal, in the majority

[17] Solidarity or group lending is a lending approach mainly used in microfinance where small groups borrow based on social collateral (rather financial collateral) to lower default risk and where peer monitoring and social sanctions are used by members to lower moral hazard in lending (Armendariz and Murdoch, 2010).

of cases, loans in the informal sector are granted on the basis of social collateral while repayment is enforced through social sanctions.

There are two significant structural changes in Kenya's credit market (Table 7). First: access to credit increased from 39.8% in 2013 to 56.9% in 2015. This increase slightly favoured the poor, among whom access to credit rose by 20 percentage points relative to 16 percentage points among the non-poor. Secondly, there have been shifts in the importance of sources of credit. In 2015, the most important sources of credit were suppliers, family and friends, microfinance institutions, shopkeepers and M-credit. However, the most important sources of credit in 2013 are family and friends, shopkeepers, microfinance institutions, *chamas* and banks. These shifts are marginalizing formal and semi-formal credit but giving more importance to informal sources of credit. Paradoxically, the main focus of public policy in Kenya is to promote the formal and semi-formal sectors, with much less focus on the informal sector. This seems to be driven by the thinking that once the formal and semi-formal segments penetrate all demographics, the (undesirable) informal sector will automatically vanish.

The latest innovation in the credit market in Kenya has been the introduction of an M-credit product called M-Shwari in 2012 through a partnership between Commercial Bank of Africa and Safaricom[18]. This product offers loans of between Ksh 100 and Ksh 20,000 at a 7.5% nominal interest rate repayable within 30 days. The launch of M-Shwari has spawned the introduction of another 20 digital credit platforms with diverse terms and conditions. For example, KCB MPESA grants loans between Ksh 50 and Ksh 1,000,000 at 14% annual interest rate which can be repaid within either 30, 90 or 180 days. Results of the FinAccess surveys

[18] This paragraph draws heavily from several blogs at http://www.cgap.org (accessed on 17th October 2017) and FSD-Kenya (2015)

show that about 10.1% of adults in Kenya have accessed a digital loan or M-credit banking product (see Table 1). This proportion is higher than the share of those who had accessed a bank loan (7.3%) and a loan from government (2.3%). Digital credit is becoming popular because, unlike traditional bank credit, the process from loan application to approval can take a minimum of a few seconds and a maximum of 24 hours. The processes are fast, automated and remote with the potential to dismantle the traditional barriers of collateral, geography and infrastructure. Despite the growing importance of M-credit in Kenya, there is little knowledge on how it is affecting traditional forms of credit. The current study will provide new evidence on how M-credit affects access to MFI credit.

4.3 Literature Review

4.3.1 Theoretical Literature

In theory, the credit market consists of the demand and the supply sides (Khoi et al., 2013; Diagne, 1999). Borrowers choose to participate in the formal credit market because they want to maximize their expected utility subject to certain constraints. The first step is choosing to participate in the credit market (Dutta and Magableh, 2006). However, choosing to participate in the credit market is not enough since the process from loan application to the granting of the loan is sequential, information-intensive and it involves different people at every stage. In the next step, the borrowers will determine how much they wish to borrow before they submit their application to the lender, who in turn decides whether to approve the loan or not. Finally, the lender determines the amount to be granted to the borrower. This chain of events illustrates the fact that whereas participation in the credit market is a demand side issue, access to the credit market is supply-driven because the lender decides to approve the loan on the basis of the borrower’s creditworthiness (Okurut et al., 2005; Zeller, 1994).

Given the absence, uncertainty and asymmetry of information (Jagun et al., 2008), allocation of resources in the credit market is therefore inefficient because the price of credit fails to equalize the supply and demand sides of the market to yield an equilibrium. In this case, equilibrium exists with an excess demand or credit rationing (Khoi et al., 2013). Quantity rationing is ideally a market failure which occurs when either the lender offers the borrower a loan amount that is less than the amount of loan demanded or completely rejects the loan application (Dutta and Magableh, 2006). Manrique and Ojah (2004) call this feature "a short supply of credit". Loan contracts are not on the basis of willing buyer–willing seller (Okurut, 2006) but are conditioned by non-price factors. Non-price factors are contingent on the amount of information the lender can access regarding the loan applicant, even though the loan applicant has an incentive to hide any undesirable behaviour that may jeopardize the approval of the loan. These information-related constraints (absence, uncertainty and asymmetry) impose market frictions, which include costs of monitoring, acquiring information and enforcing contracts (Cordella, 2006). These frictions prevent the lenders from being perfectly informed about the default risk associated with the loan applicant and the project being financed (Stiglitz and Weiss, 1981). These problems lead to excess demand in the formal financial market, which in turn gives room to the evolution of informal institutions (Okurut et al., 2005). Unlike their counterparts in the formal sector, informal lenders rely on relationship lending whereby group dynamics, joint liability, reputational capital, social collateral and repayment incentives are used to forestall problems of adverse selection and moral hazard in lending (Khoi et al., 2013).

Microfinance institutions tend to have a pro-female bias (Armendariz and Morduch, 2010). According to Ledgerwood (1999), MFIs take a special interest in women relative to men because the former are relatively poor, are responsible for child-bearing and have fewer income-earning opportunities. In addition, they target women because this enables them to accomplish the dual objectives of achieving high repayment rates and meeting social goals (Armendariz and Morduch, 2010). This outcome is perpetuated by gender segregation backed by patriarchal social structures (Mpuga, 2010). Such structures tend to confer differential power to the sexes with men having superior rights over collateralizable assets such as land. In some cases, women are turned away from banks when they apply for loans based on the perception that they are unable to control household income (Ledgerwood, 1999; Armendariz and Morduch, 2010). D'espallier et al. (2011) has provided evidence to show that a higher proportion of women in the gross loan portfolio is significantly correlated with lower non-performing loans, fewer loan losses and lower provision for doubtful debts. This evidence indicates that women are better credit risks compared to their male counterparts.

The theoretical basis of the pro-female bias in microfinance is threefold (Armendariz and Morduch, 2010). First, financial discrimination theories suggest that women have restricted access to financial markets. Since women have less access to capital than men, the neoclassical theory predicts that the return to capital for women should be higher than for men. Secondly, according to the labor mobility thesis, women tend to be more occupationally immobile compared to men. This is because they stay at home and work near home. Less mobility lowers the incidence of strategic default under the fear of social sanctions. This makes it easier and less costly to monitor their loans. Lastly, women tend to be more risk averse than men (Parker, 2018). Being less mobile, avoiding social sanctions, being less likely to divert their loans towards unproductive activities and being risk averse determine the type investment projects that women undertake. Such investments will tend to have more predictable returns, making women better borrowers because the chances for default are fewer.

Lifecycle theory of consumption suggests that age is a critical factor affecting demand for loans. According to Deaton (2012), young and old people borrow more because their income is less than their consumption while middle income people save more because their income exceeds consumption. Young people tend to save so that they have money to spend during their retirement. In terms of wealth, very young and very old people have little wealth. Peak wealth is achieved just when people retire. As they get much older, retirees tend to shed off their wealth to provide for food, housing and recreation. These assets are taken up by the young, who still have an appetite for wealth. The assets follow a life-cycle pattern changing hands from the old to the young over time.

Human capital theory, which has its origins in the neoclassical paradigm, postulates that educated and trained people are more productive because they possess skills, knowledge, values and habits that they acquire in school (Quiggin, 1999). Educated individuals have more assets, higher incomes and are more likely to engage in business activities. In relation to credit markets, educated people are more likely to appreciate the benefits and cost of credit compared to non-educated individuals. In addition, they can readily obtain financial information on sources of loans, the borrowing process, the terms of the loans and so on. They may also possess better book keeping and management skills which enable them to maintain proper loan books and service their loans.

Social capital theory has popularized group lending technologies in microfinance. Solidarity or group lending is a lending approach mainly used in microfinance where small groups borrow based on social collateral (rather financial collateral) to lower default risk and where peer monitoring and social sanctions are used by members to lower moral hazard in lending

(Armendariz and Murdoch, 2010). Membership in a group is used as collateral to help the poor access capital for investment (Fernando, 2006). Viewed from this perspective, groups become avenues through which transaction costs are reduced and women are empowered. Solidarity groups are able to lower transaction costs because they foster communication and information-sharing. The dense associational networks in groups makes them an avenue for knowing more about the behaviour of other members as well as lenders. Under group formation, members exchange information, apply social sanctions and use joint liability as mechanisms for reducing informational problems in lending. In terms of empowerment, microcredit helps members, mainly women, to engage in income-earning activities thus reducing their dependence on their spouses.

Distance theory postulates that long distance between a borrower and a lender can act as an access barrier because of the escalation of transaction costs, monitoring costs and information asymmetry (Weber et al., 2012). Quite often, rural areas suffer from geographical isolation due to infrastructural deficiencies. In addition, they tend to have a less diversified economic structure and are exposed to covariant risks. Therefore, people in rural areas suffer from informational challenges – availability, quality and asymmetry. Due to infrastructural bottlenecks, individuals located in rural areas tend to travel long distances to access banking services. Offering mobile-based financial services affords them low-cost, safe and secure financial services (Qiang et al., 2012). Mobile phones also help to forestall problems of information asymmetry. They help people communicate with one another, obtain information on prices and quality and break into new markets (West, 2012).

4.3.2 Empirical Literature

Several studies have examined the factors that determine access to credit (Li et al., 2011; Khoi et al., 2013; Mohieldin and Wright, 2000; Akoten et al., 2006; Okurut, 2006; Dutta and Magableh, 2006 and many others). These determinants can be grouped under five broad categories: individual characteristics, household characteristics, financial factors, sector-level attributes and macro-institutional factors. The most common factors identified in the literature fall under individual and household characteristics. These include age, gender, marital status, religion, schooling, employment status, ethnic group, race, occupation, wage, risk aversion and group membership.

Age is usually included in studies on credit to capture life-cycle effects which have been hypothesized to be non-linear and therefore accommodated by the inclusion of age and age-squared terms in the same regression (Okurut, 2006; Dutta and Magableh, 2006; Campbell, 2006; Manrique and Ojah, 2004; Kimuyu and Omiti, 2000; Steiner et al., 2009). Generally, old and young people borrow more compared to middle aged persons. Young people borrow more because their consumption exceeds their income. They borrow in order to finance their schooling and human capital investments. Middle aged people are economically active and tend to borrow less since their income exceeds their savings. Older persons may rely more on dis-savings than on loans to finance their consumption needs. Okurut et al. (2005) shows not only that older individuals are more likely to apply for informal sector loans, but they also demand and receive bigger loans and they are less likely to be credit rationed. This can be attributed to the effect of social networks among old people who tend to have more friends and acquaintances than young people. However, when the loan application process is analysed sequentially from application, loan screening, approval and disbursement, Mpuga (2000) shows that this does not necessarily hold. He finds that age non-linearly determines the probability of applying for credit as well as the amount applied for. However, age has no effect on the likelihood that the application is successful and does not determine the amount received. Barslund and Tarp (2008) find that a 1% increase in the age of the household head increases the probability of borrowing by 0.41%.

Gender is usually included in demand for loans regressions to account for the effects of social norms that affect power relations between the sexes and segregate economic activities (Dutta and Magableh, 2006). Empirical evidence is not agreed on the direction and magnitude of the effect of the gender factor on access to credit. Barslund and Tarp (2008) find that being male rather than female lowers the probability of borrowing while Manrique and Ojah (2004) establish that being male rather than female increases the probability of being credit unconstrained. According to the latter study, being male rather than female increases the propensity of being unconstrained by 7.1 percentage points. However, men have 1.1% and 1% lesser chance of holding a consumption loan and real estate loan, respectively. Zeller (1994) shows that being male rather than female increases both the chance of being credit constrained as well as being more likely to apply for credit. Kenyan and Ugandan evidence is provided by Johnson and Nina-Zarazua (2009). In Kenya, gender does not affect the likelihood that one is formally included in the financial sector but being male rather than female increases the likelihood of being financially included in the informal sector. In Uganda, those who are included in both formal and informal sectors are more likely to be men rather than women. In Jordan, Dutta and Magableh (2006) show that men are less likely to apply for microcredit compared to women. However, the gender factor is not important in determining the demand for microcredit and the probability of being credit-constrained.

Empirical evidence on the effects of education on access to credit is mixed. Education level accounts for human capital endowment (Bending et al., 2009) and management ability (Dutta and Magableh, 2006). In Kenya and Uganda, evidence indicates that educated individuals have higher chances of being financially included in formal and informal sectors compared to those with no formal education (Johnson and Nina-Zarazua, 2009). Zeller (1994) shows that both the probability of being credit constrained and the probability of applying for credit are positively and significantly correlated with years of schooling. Evidence from South Africa shows that education is positively and significantly correlated with the access to bank and formal credit but is negatively and significantly correlated with informal credit (Okurut, 2006). However, schooling has no effect on access to semi-formal credit. Using Chinese data, Cheng (2007) finds that years of schooling have no effect on the demand for microcredit. However, the years of schooling among housewives reduces the demand for microcredit. In fact, an extra year of schooling lowers the propensity to borrow by 1.8%.

Family business theory postulates that married individuals who are in business are more likely to attract their spouses into business (Simoes et al., 2016). Marriage tends to pool the networks, acquaintances, assets, skills and knowledge of the couple (Taniguchi, 2002; Wu and Wu, 2015; Parker, 2018). Being married reflects stability, responsibility and maturity (Mpuga, 2010) while being single may reflect independence from family (Dutta and Magableh, 2006). These facts suggest that married individuals may receive more favourable treatment in credit markets compared to their unmarried counterparts. Effects of marriage on participation in credit markets is mixed. Dutta and Magableh (2016) find that being single compared to being married, separated, widowed etc, increases the likelihood of applying for a loan and demand for credit but has no effect on the likelihood of being credit constrained and on the supply of credit. Duy et al. (2012) confirm that marriage is a predictor of credit access in Vitenam. Mpuga (2010) shows that being married rather than being single increases the likelihood of applying for credit, the amount of credit demanded, the success of the loan application and the amount of credit supplied.

Usually, larger families not only increase the rate of time preference (Manrique and Ojah, 2004) but they also increase dependency (Li et al., 2011; Duta and Magableh, 2016). This means that such families tend to have higher consumption in the present period rather than in the future. This consumption pattern increases the burden of the household head to provide for the family, which increases the probability of loan default, and thus lowers access to credit. Evidence, however, shows that this is not necessarily true. Nguyen (2005) shows that household size increases the propensity of borrowing but does not affect the amount of loan received while Pal (2002) finds that household size enhances the demand for both formal and informal rural credit in India. Mpuga (2010) finds that household size negatively and significantly predicts the probability to apply for microcredit, the probability of the application being successful and the amount of loan applied for. Okurut et al. (2005) shows that the dependency ratio is positively correlated with the likelihood of applying for a loan from the informal sector and the amount of loan demanded. Swain (2007) finds that dependency significantly predicts the supply of credit but does not predict the demand for credit. Crook (2001) shows that household size negatively affects the likelihood of not being credit constrained.

Financial and wealth considerations have also been hypothesized to affect access to credit. These factors include collateral value (Atieno, 1997), total value of assets owned and income (Diagne, 1999; Li et al., 2011; Mohieldin and Wright, 2000; Campbell, 2006), loan default

(Barsland and Tarp, 2008), remittances (Steiner et al., 2009) and many others. In credit regressions, financial factors are included to account for the capacity to repay the loan, measure the strength of previous business relationships and assess the reputation of the borrower (Okurut, 2006). Individuals with more income and assets will have access to credit markets because they are able to raise the collateral required by lenders. Evidence from Kenya and Uganda shows that household assets are significant predictors of both financial inclusion in both formal and informal markets (Johnson and Nina-Zarazua, 2009). Li et al. (2011) find that a one-unit increase in assets lowers the probability to borrow by 0.6 percentage points while a one instant rise in income increases the probability to borrow by 0.12 percentage points. Mohieldin and Wright (2000) find that ownership of assets lowers the likelihood of borrowing from formal sources but it increases the likelihood of borrowing from informal sources. Campbell (2006) finds that wealth has no significant effect on the probability of holding both public and private equities. However, income significantly lowers the propensity of holding private equity but increases the propensity of holding public equity.

One of the main functions of credit markets is to facilitate the trade, diversification and management of risk (Moyi, 2013). This explains why households resort to financial markets as a shock coping mechanism. Such shocks include illness, floods, drought and death (Diagne, 1999; Zeller, 1994; Steiner et al., 2009; Barsland and Tarp, 2008). Steiner et al. (2009) find that households that had experienced death of a member in the previous 5 years were more likely to save. However, those households that experienced illness of a member within the previous 5 years were more likely to borrow and purchase insurance. Households that experienced any other shocks, were more likely to save and borrow but less likely to purchase insurance. Barsland and Tarp (2008) do not establish any significant role for hospitalisation (as a proxy for shocks) in the propensity to borrow by households in Vietnam.

Geographical factors include distance between the household and the nearest financial institution (Li et al., 2011; Nguyen, 2005; Swain, 2007), area terrain (Bhanot et al., 2012) and location (Mpuga, 2010; Duy, 2012; Crook; 2001). One of the main advantages of MFS is the reduction of costs related to distance and transactions. Households that are located in rural areas are more exposed to covariate risks, have a less diversified economic base and experience higher transaction costs (Ledgerwood, 1999). Li et al. (2011) find that households that are located over 10 kilometres from the financial institution are less likely to borrow from the Chinese rural microcredit markets. Specifically, being located over 10 kilometres from the financial institution compared to being located less than 10 kilometres reduces the likelihood of borrowing by 24% points. In India, Bhanot et al. (2012) find that distance from the bank does not significantly affect financial inclusion but the distance between the household and the post office negatively affects financial inclusion. Nguyen (2005) finds that distance to Government banks and the bank for Agriculture and Rural Development were not significant predictors of the propensity to borrow as well as the demand for credit. Swain (2007) establishes a negative and statistically significant correlation between distance from the bank, on one hand, and the propensity to borrow and the loan size, on the other hand. The same study establishes a negative correlation between distance from the cooperative, on one hand, and the propensity to borrow and the size of the loan, on the other hand.

Some studies have analysed the role of location in urban areas in the borrowing decision. Khoi et al. (2013) finds that being located in urban communes rather than rural ones lowers the propensity to borrow from both formal and informal credit markets. Okurut (2006) finds that households that are located in rural areas are less likely to access bank credit compared to their urban counterparts. When the different types of credit are compared, the study finds that being located in a rural area rather than an urban one lowers access to formal, semi-formal and informal credit markets. Mpuga (2010) finds that being located in a rural area does not affect the probability of applying for credit and the amount applied. However, rural households receive much less credit compared to their urban counterparts.

The studies that have been reviewed in this section show that the predictors of access to credit include individual, household, financial and geographical factors. However, no previous study has analysed the effect of MFS on access to credit. To fill this gap in knowledge, this study focuses on the effect of MFS on access to MFI credit in Kenya. Consistent with transaction cost theory and distance theory, digital platforms have the effect of reducing search and coordination costs without increasing transaction risks (Weber et al., 2012). Distance theory is premised on the idea that monitoring costs and information asymmetry increase in direct proportion to the geographical distance between the lender and the borrower. Microfinance is a transaction-intensive sector involving, in some cases, many poor clients transacting very small loans but spread over wide geographical areas. In such cases, MFS have the potential to reduce all these costs and therefore bridge the distance between the borrower and the lender.

4.4 Methodology

4.4.1 Data Type and Sources

This study uses the 2013 and 2015 Kenya FinAccess survey data collected by the Financial Access Partnership comprising the Central Bank of Kenya (CBS), Kenya National Bureau of Statistics (KNBS) and Financial Sector Deepening (FSD) Trust. These surveys targeted adults above the age of 16 with the aim of generating quantitative measures of access to and demand for financial services in Kenya using nationally representative samples. Representativeness is achieved by using the National Sample Survey and Evaluation Program V (NASSEP V) sampling frame constructed by KNBS. Sampling followed a three-stage process. At the first stage, 710 (in 2013) and 834 (in 2015) clusters were selected from the NASSEP V frame. At the second stage, 12 households (in 2013) and 14 households (in 2015) were selected in each cluster. Finally, 8520 (in 2013) and 10,008 (in 2015) individuals were selected to be interviewed. In 2013 and 2015, the response rates were 80% and 87% respectively. A structured questionnaire was the main tool used to collect data. Questionnaires were administered to all adult members of the sampled households.

The two surveys are not directly comparable for two reasons. Firstly, they are not a panel; the responses in 2013 and 2015 were not derived from the same individuals. Lastly, the questionnaires used in 2013 and 2015 were different. Even for the same variables, there were differences in coding and the 2015 questionnaire had more questions compared to the 2013 one. Therefore, it was not possible to pool the data from the two surveys. This explains why analysis in the proceeding sections is presented separately for each year.

4.4.2 Model Specification

Many studies that examined the determinants of access to credit used probit (Khoi et al., 2013; Mohieldin and Wright, 2000; Akoten et al., 2006; Campbell, 2006; Cheng, 2007 and many others), logit (Li et al., 2011; Okurut, 2006; Dutta and Magableh, 2006 and many others) and multinomial logit approaches. Depending on study focus, some authors have used a combination of these three methods (Okurut, 2006; Mpuga, 2010; Okurut et al., 2005). The current study, following the relevant literature also treats access to microcredit as a binary variable. In these studies, access to credit is considered a discrete choice problem where the respondent has either used the service or not – conditional on household characteristics, individual characteristics, institutional factors, infrastructural factors and so on.

In this study, the outcome variable (y) represents the probability of borrowing from an MFI. Variable y takes a value of 1 if a household has ever used credit from a microfinance institution[19] and 0 otherwise. As described by Cameron and Trivedi (2010), this can be expressed below;

$$y = \begin{cases} 1 & with\ probability\ p \\ 0 & with\ probability\ 1-p \end{cases}$$

The outcome variable (y), follows a Bernoulli distribution, with one tail. If the probability of using MFI credit by individual i is p_i, then the probability of not using MFI credit will be (1 - p_i). This implies that the discrete probability density function is

$$f(y_i|x_i) = p_i^{y_i}(1-p_i)^{1-y_i}, \qquad y_i = 0,1 \tag{7}$$

Where $0 \leq p_i \leq 1$, $E(y_i) = p_i$ and $Var(y_i) = p_i(1-p_i)$. For regression purposes, the probability p varies across individuals and households given the regressors. Given equation (7), the conditional probability of p_i can be expressed as

$$p_i = \Pr(y_i = 1|x) = F(x_i'\beta) \tag{8}$$

Where x is a K×1 vector of independent variables, β is a vector of unknown coefficients for independent variables and $F(.)$ is a cumulative density function on (-∞, +∞). Assuming that $F(.)$ is a standard normal cumulative density function yields a probit model, which is specified in equation (9).

[19] FinAccess (2016) defines an MFI as a financial provider who is legally registered and/or operates through direct government interventions. This excludes microfinance banks. Microfinance banks are subject to all banking regulations making them less likely to focus on the social mission. For purposes of this study, access to loans from SACCOs and MFIs were collapsed to yield the variable *MFI loan*. The questionnaire captured these two strands separately.

$$p_i = \Pr(y_i = 1|x) = \Phi(x_i'\beta) = \int_{-\infty}^{x_i'\beta} \phi\,(z)dz = \int_{-\infty}^{x_i'\beta} \frac{1}{\sqrt{2\pi}} \exp(^{-z^2}/_2)\, dz \qquad (9)$$

Vector x contains independent variables, which include age, gender, marital status, schooling, monthly income, household size, location, M-money, M-banking and M-credit. These variables are defined in Section 4.4.3.

In equation (9), it is suspected that access to credit and monthly income are jointly determined. Unobservable shocks that affect an individual's decision to borrow also affect the individual's income. Therefore, income is endogenous. This means that any probit estimates obtained from equation (9) will be inconsistent (Wooldridge, 2013). Therefore, this study adopts an instrumental variable technique to deal with the econometric problem of endogeneity. The study used two instruments. For the 2013 dataset, the number of rooms the household occupies is used as an instrument. For the 2015 dataset, the study used the time taken to complete the questionnaire as the instrument. The use of number of rooms occupied by the household is justified by the fact that people with higher incomes tend to occupy houses with more rooms. However, their decision to live in more rooms is unrelated to their desire to take out a loan. One may argue that a house is a collateralizable asset, which invalidates its use as an instrument. Whereas this argument may hold regarding bank credit, it does not hold in the case of microcredit since many studies show that social collateral (by use of joint liability or availability of a guarantor) is more important than financial collateral (Armendariz and Murdoch, 2010). Hence, it can be argued that financial collateral is not directly correlated with the decision to obtain MFI credit although an indirect link can be inferred. Again, if the household occupies a rented house or a house that is not permanent, then the collateral argument breaks down because such a house cannot be used as loan collateral. Similarly, the use of duration (or the time taken to complete the questionnaire) as an instrument for income can be justified on the basis that people with higher incomes are more educated and have higher cognitive skills. This being the case, there are two possible outcomes. First: compared to people with lower cognitive skills and low incomes, these respondents tend to be more inquisitive when confronted with a questionnaire, which may extend the interview sessions. In the second case, people with higher incomes and with higher cognitive skills can understand the questions faster and will take a shorter time to complete the questionnaire. Given this ambiguity, this instrument was subjected to the data in order to determine the direction of the relationship and its validity. The results are discussed in Section 4.5.2.

4.4.3 Definition of Variables

The main focus of this study is to determine the extent to which MFS affect access to microfinance credit, controlling for individual and household characteristics. The dependent variable is *MFI loan*, which is a dummy variable that takes a value of 1 if a household has ever used a loan from a microfinance institution and 0 otherwise. Mobile-based financial services are captured by three variables: *M-money*, *M-banking*, *M-credit*. *M-money* is a dummy variable that takes 1 if a respondent has ever used M-money and 0 otherwise. Likewise, *M-banking* is coded 1 if the respondent has ever used the financial service and 0 if not. *M-credit* takes a value of 1 if the respondent has ever received credit from either M-Shwari or KCB MPESA and 0 otherwise. Individual factors include income, age, gender, household conditions, marital status and education level.

During the two periods, *income* was measured slightly differently; the 2013 and 2015 income measures may not be directly comparable. In 2013, income was captured as gross monthly earnings (in Kenya shillings) while in 2015, it was captured as monthly income (in Kenya shillings). In all regressions, income, age and household size are used in their log-normalized form. The variable *age* is measured in years. Gender is captured by the variable *male* which takes the value 1 if the respondent is male and 0 if female. Marital status is captured by the variable *married*, which is coded 1 if the respondent is married or living with a partner and 0 if single, divorced/separated and widowed. Education achievement is captured by the variable *education*, which takes the value 1 if the respondent completed either primary, secondary or tertiary schooling and 0 otherwise. The study accounts for two household factors: size and location. *Household size* is captured by the number of members in a household. Location of the household is captured by the variable *rural* which is coded 1 if the household belongs to a rural cluster and 0 otherwise. In 2013, poverty was determined by applying the KNBS poverty line. However, in 2015, poverty was measured by applying wealth quintiles. Quintiles were formed after constructing a wealth index using a principal components technique. This technique constructs a composite wealth index using the first principal component of a vector of assets (durable goods, housing characteristics and access to utilities). Any household that falls in the 1st and 2nd quintile was considered to be poor while one that fell in either 3rd, 4th or 5th quintile was considered non-poor.

4.5 Empirical Results

4.5.1 Descriptive Statistics

Summary statistics of the variables used in the regressions are presented in Appendix Table A10. The results show that penetration by MFIs in Kenya has increased from around 10% in 2013 to 11% in 2015. Compared to microfinance products, the market reach of M-money is significantly higher and the growth of M-money penetration is also much faster than the growth of MFI penetration. Between 2013 and 2015, the use of M-money had grown from about 62% to 69%. The use of M-banking and M-credit is also growing in importance. It is notable that even though the first M-credit product was launched in Kenya in 2012, about 10% of Kenyans had accessed M-credit by 2015.

Mean income is Ksh 16,092 (approximately USD 161) in 2015 and Ksh 7,228 (approximately USD 72) in 2013. The standard deviation in 2015 is Ksh 181,685 (approximately USD 1817), which is almost 11 times the mean. In 2013, the standard deviation is Ksh 17,526 (approximately USD 175), which is almost twice the mean. It can be concluded that income is very highly dispersed across individuals as shown by the high standard deviations. Similarly, comparisons between mean incomes (Ksh 16,092 in 2015 and Ksh 7,228 in 2013) and median incomes (Ksh 6,000 or USD 60 in 2015 and Ksh 3,000 or USD 30 in 2013) shows that this variable is considerably skewed and has thick tails. This also implies most incomes are concentrated within the lower percentiles. The same applies to age and household size. This partially explains why these variables (income, age and household size) were log normalized before being used in the regressions.

The sample has more women than men (59% in 2013, 61% in 2015), more urban than rural households in 2013 (64%) but more rural than urban households in 2015 (56%). Most respondents are educated (85% in 2013, 82% in 2015) and are married (64% in 2013, 60% in 2015). The level of poverty is high (over 30% in both periods) and highly variable.

4.5.2 Regression Results

Before running the regressions, the data was checked for pairwise correlations of the regressors. Appendix Tables A11 and A12 show that most of the coefficients fall below 0.5, which implies that multicollinearity is not a serious problem in the regressions. In 2013, the highest correlation coefficient is 0.344 between education and M-money, which does not pose any multicollinearity concerns. In 2015, the highest correlation coefficient was 0.670 between M-credit and M-banking. The coefficient 0.670 is high and suggests that inclusion of both M-credit and M-banking in a regression could occasion multicollinearity. Therefore, the two variables are entered in the regressions separately. As explained in Section 4.4.2, income is endogenous. This is due to the suspicion that reverse causality between credit and income is likely to compromise the consistency of the coefficient estimates. Given these concerns, instrumental variable estimators are adopted to forestall this problem. For income, the instrument must satisfy two conditions (Wooldridge, 2013). Firstly, the instrument should be uncorrelated with the error term generated from equation 3. Secondly, the instrument should be highly correlated with income - referred to as "instrument validity". This study used the number of rooms occupied by a household (for 2013 data) and the time taken by a respondent to complete the questionnaire, or duration, (for 2015 data) as instruments for income.

Diagnostic statistics are reported in the bottom rows of each table. For each regression model, three assessments were conducted: (1) instrument validity tests, (2) tests for endogeneity of income and (3) likelihood ratio tests of the statistical significance of the regressions. Testing the validity of the number of rooms as an instrument for income using a reduced form equation yields a coefficient of 0.18 ($p<0.05$). Therefore, the null hypothesis (H_0 = instrument is not valid) is rejected, which means that the instrument is relevant for explaining variations in income. The coefficient on duration is 0.56 ($p<0.05$), which indicates that the time taken to complete the questionnaire has a statistically significant positive correlation with income. Duration passes the instrument validity test. Tests for the endogeneity of income are reported in Tables 7, 8 and 9. For all probit estimations[20], the Wald tests for exogeneity (H_0 = income is exogenous) have p-values falling below 0.10. This leads to the rejection of H_0 at the 10% level implying that income is endogenous, which justifies the use of instrumental variable estimators as they yield more consistent estimates. Likelihood ratio chi-squared (LR Chi2) and the associated p-values of <0.05 show that the null (H_0 = all the coefficients associated with

[20] Stata output for 2SLS does not report exogeneity test results.

independent variables are simultaneously equal to zero) is rejected at conventional levels of significance. The models are statistically significant as suggested by the Chi2 test statistic.

4.5.2.1 Results Based on FinAccess 2013 Data

Regression results based on 2013 data are presented in Table 8. Baseline findings for the whole sample are reported in column (a). Columns (b) and (c) report baseline results by poverty status. For comparison, instrument variable two stage least squares (hereafter, IV 2SLS) results are reported in columns (d), (e) and (f). Baseline findings in column (a) show that the coefficient on M-money is positive but statistically insignificant. However, the coefficient on M-money among the non-poor is positive and statistically significant (column c) but this coefficient is statistically insignificant among the poor (column b) suggesting that non-poor respondents who use M-money are more likely to use MFI credit. This implies that M-money plays a complementary role in accessing MFI credit only among the non-poor. On average, changing from not using M-money to using M-money increases the probability of accessing MFI credit by 3% among the non-poor (column f). However, the IV 2SLS results show that these IV probit estimates are not robust.

Table 8: IV estimates of the probability of using MFI credit (2013)

	Dependent variable: Dummy = 1 if ever used MFI loan, 0 otherwise					
	IV Probit			IV 2SLS		
	(a)	(b)	(c)	(d)	(e)	(f)
	All	Poor	Non-poor	All	Poor	Non-poor
M-money	0.01	-0.19	0.33***	-0.05**	0.04***	0.03*
	(0.104)	(0.134)	(0.107)	(0.025)	(0.011)	(0.017)
Income	0.83***	1.40***	0.95***	0.24***	0.03	0.26***
	(0.044)	(0.054)	(0.098)	(0.038)	(0.022)	(0.040)
Age	-1.14	-3.09	1.86	-0.96***	0.27	0.08
	(1.299)	(1.982)	(1.542)	(0.314)	(0.165)	(0.267)
Age squared	0.21	0.46*	-0.20	0.14***	-0.03	-0.00
	(0.177)	(0.270)	(0.211)	(0.044)	(0.023)	(0.037)
Male	-0.33***	-0.10	-0.26***	-0.09***	-0.01	-0.06***
	(0.046)	(0.076)	(0.057)	(0.019)	(0.011)	(0.016)
Married	-0.02	-0.17**	0.19***	-0.03*	-0.00	0.03**
	(0.064)	(0.070)	(0.072)	(0.016)	(0.011)	(0.013)
Education	-0.10	-0.15	0.16	-0.05**	0.01	0.01
	(0.104)	(0.099)	(0.142)	(0.023)	(0.014)	(0.022)
HH size	0.06	0.01	0.03	0.02***	-0.02**	0.01
	(0.035)	(0.077)	(0.045)	(0.009)	(0.010)	(0.010)
Rural	-0.31***	-1.13***	-0.52***	-0.09***	-0.02	-0.14***
	(0.053)	(0.096)	(0.095)	(0.020)	(0.023)	(0.030)
No. of obs.	5,068	1,062	3,636	5,077	1,434	3,643
Chi2	999	1382	519	266	38	292
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Exogeneity test	0.000	0.097	0.000	0.000	0.142	0.000

The dependent variable is usage of MFI credit dummy. Robust standard errors are reported (in parentheses). ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. All regressions include a constant and county[21] dummies, which are not reported. However, the IVSLS regression in column 6 does not include county dummies in the main regression but does so in the auxiliary regression. Exogeneity test for IV 2SLS is the Durbin-Wu-Hausman test as described in Cameron and Trivedi (2010).

Apart from M-money, the 2013 results in column (a) show that the determinants of access to MFI supplied credit in Kenya are income, gender and type of cluster (rural/urban). However, analysing the sample by poverty status gives slightly varied results, especially among the non-poor. Among this demographic, respondents with higher incomes, women, married individuals

[21] Counties are administrative units. Administratively, Kenya has one national government and 47 county governments.

and those residing in urban areas are more likely to use MFI supplied credit. However, the poor who use MFI credit have higher incomes, are female, married and reside in urban areas.

Income is associated with a significantly higher propensity for MFI credit. This effect is robust to different estimators (IV probit and IV 2SLS) and varies by poverty status. Given that the mission of MFIs is to provide loans to the poor, the positive and significant effect of income on access to MFI credit should be of concern. It may indicate that microfinance is serving the non-poor (who have higher incomes) at the expense of the poor who should be the main beneficiaries. This result corroborates Crook's (2001) and Turvey and Kong's (2010) findings of a positive relationship between demand for microcredit and income.

The coefficient on the male variable is negative and statistically significant (column a). On average, being male is associated with a lower probability of using MFI credit. This finding is robust to IV probit and IV 2SLS estimators. This result is expected because women constitute about 62% of the MFI clients in Kenya (AMFI, 2013). The focus on women by MFIs is guided by the empirical fact that they are better credit risks compared to men (D'espallier et al., 2011). Women are targeted by MFIs because they represent a large proportion of the poorest segment of the society and they have fewer economic opportunities (Ledgerwood, 1999) occasioned by lopsided power relations and family structures that disenfranchise them.

Results in column (a) show that the type of cluster significantly impacts access to microcredit, which is consistent with Mpuga (2010). On average, being located in a rural area compared to being located in an urban area decreases the probability of using MFI credit. However, this effect is stronger among poor respondents compared to their non-poor counterparts, implying that there is a possibility that rural households do not benefit much from the expansion that has been witnessed in microfinance markets. Given that MFIs target poor households who are predominantly based in rural areas, this result is surprising. It may be explained by the fact that many MFIs, like traditional banks, are located in urban areas, making them less accessible to rural households.

4.5.2.2 Results Based on 2015 FinAccess Data

Regression results based on 2015 data are reported in Table 9. Results from baseline IV probit regressions are reported in columns (a), (b) and (c). To establish robustness of the findings, IV 2SLS results are presented in columns (d), (e) and (f). Diagnostics are reported at the bottom of Table 8. Chi square tests suggest that the models are statistically significant. For estimation results, the Wald tests for exogeneity (H_0 = income is exogenous) have p-values falling below 0.05. Therefore, H_0 is rejected at the 0.05 level implying that the income is endogenous. The use of instrumental variable estimators is thus empirically supported.

Most of the explanatory variables are statistically significant and have the expected signs, except for age which is negative. Specifically, the results show that probability to use MFI credit is lower among those using M-banking and M-credit as well as among males and married persons. However, higher income, being educated, higher household size and being located in a rural cluster is associated with a higher probability to use MFI credit. In, addition, the results suggest a U-shaped relationship between the probability of using MFI credit and age.

Table 9: Estimates of the probability of using MFI credit (2015) – Baseline results

	Dependent variable: Dummy = 1 if ever used MFI loan, 0 otherwise					
	(a)	(b)	(c)	(d)	(e)	(f)
	IV Probit	IV Probit	IV Probit	IV 2SLS	IV 2SLS	IV 2SLS
M-money	-0.00			-0.06***		
	(0.076)			(0.018)		
M-banking		-0.18***			-0.04**	
		(0.055)			(0.019)	
M-credit			-0.20***			-0.03
			(0.060)			(0.022)
Income	0.85***	0.84***	0.84***	0.23***	0.22***	0.22***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.024)	(0.024)
Age	-2.10*	-2.35*	-2.45*	-1.83***	-1.96***	-1.94***
	(1.270)	(1.343)	(1.329)	(0.323)	(0.347)	(0.342)
Age square	0.38**	0.41**	0.42**	0.27***	0.28***	0.28***
	(0.168)	(0.178)	(0.176)	(0.045)	(0.048)	(0.047)
Male	-0.39***	-0.38***	-0.39***	-0.09***	-0.09***	-0.09***
	(0.033)	(0.033)	(0.033)	(0.014)	(0.013)	(0.013)
Married	-0.14***	-0.14***	-0.14***	-0.04***	-0.04***	-0.04***
	(0.040)	(0.040)	(0.041)	(0.012)	(0.012)	(0.012)
Education	0.15*	0.14*	0.14*	0.03*	0.02	0.02
	(0.079)	(0.083)	(0.083)	(0.015)	(0.016)	(0.016)
Household size	0.11***	0.11***	0.12***	0.04***	0.04***	0.04***
	(0.027)	(0.027)	(0.027)	(0.008)	(0.008)	(0.008)
Rural	0.15***	0.15***	0.15***	0.04***	0.04***	0.04***
	(0.036)	(0.036)	(0.037)	(0.011)	(0.011)	(0.011)
No of obs.	8,142	8,142	8,142	8,529	8,529	8,529
Chi2	2833	2769	2719	672	681	692
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Exogeneity test	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is usage of microcredit dummy. IV refers to instrumental variable. Robust standard errors are reported (in parentheses). ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. All regressions include a constant and county dummies but are not reported. n/a refers to not applicable. Exogeneity test for IV 2SLS is the Durbin-Wu-Hausman test as described in Cameron and Trivedi (2010).

The results in columns (b) and (c) show that the use of M-banking and M-credit is associated with lower probability of using MFI credit. However, column (a) shows that the coefficient on M-money is not statistically significant. The predicted probability of borrowing from an MFI is on average around 0.04 lower for those who have ever used M-banking compared to those who have never used M-banking. On average, using M-credit, compared to not using M-credit, decreases the probability of using microfinance credit by 0.03. These results suggest that M-money and M-credit, on one hand, and MFI credit, on the other hand, are substitutes. The fact that M-money and M-credit give users an advantage in terms of low transaction costs, fast speed and few distance barriers compared to use of MFI credit explains this preference.

The coefficients on income, male and rural are statistically significant in 2013 and 2015. Whereas income and male have the same signs during the two periods, the sign of the coefficient on rural is inverted in 2015. In this year, the predicted probability of borrowing from an MFI is, on average, around 4% higher for households located in rural areas than for households located in urban areas. Results for the entire sample show that the coefficient on income is significantly positive and robust in all regressions implying that a higher level of income increases the propensity to use MFI credit. The increase in probability of using MFI credit for one-unit increase in log income is 23 percentage points. This result is consistent with Mohieldin and Wright (2000) who found that those who obtained formal sector loans tended to have high incomes. The result is also consistent with Johnson and Nina-Zarazua (2009), Campbell (2006), Crook (2001) and Turvey and Kong (2010).

Age has a significantly non-linear relationship with the propensity to use MFI credit. This lifecycle effect follows a U-shape pattern. The results reveal a statistically significant negative impact of age on the likelihood of borrowing from an MFI. According to column (d), the probability of using MFI credit decreases with age until a threshold of 29.4 years, when this effect is reversed. After this age, older people are more likely to use MFI credit than younger ones. This finding is consistent with Okurut (2006), Campbell (2006) and Dutta and Magableh (2006) but contrasts many other studies that have established a concave relationship (Mpunga, 2010; Zeller, 1994; Kimuyu and Omiti, 2000) where the signs on the coefficients for age and age squared are positive and negative, respectively.

The coefficient on the marital status variable is negative, statistically significant and robust in all regressions. On average, being married compared to being unmarried (which includes single, widowed, divorced and separated) decreases the probability of using microfinance credit by about 4%. The negative effect of marital status on propensity to borrow from an MFI is surprising and inconsistent with Khoi et al. (2013), Mpuga (2010), Dutta and Magableh (2006) and Akoten et al. (2006) who found a positive relationship between marriage and the propensity to borrow. This is because financial institutions view married people as more stable and reliable. The negative effect may be explained by the fact that married individuals are less independent since they have to consult their spouses before taking out a loan. The same does not apply to single, widowed, divorced and separated individuals who make unilateral loan decisions.

Education increases the likelihood that the individuals have used MFI credit. The predicted probability of using MFI credit is on average around 3% points higher for those with formal education than for those without formal education. This is explained by the fact that education enhances the financial literacy and numeracy skills of individuals. Educated people have more skills and exposure to the external environment including risks (Li et al., 2011), pursue profitable entrepreneurship, understand the workings of credit arrangements and successfully manage loans (Kimuyu and Omiti, 2000). These factors enhance their demand for credit. This finding corroborates Johnson and Nino-Zarazua (2009) who found that the likelihood of educated people being financially excluded is much less compared to those without formal education. A positive and significant relationship between education and access to credit is also supported by Li et al. (2011), Khoi et al. (2013), Shem et al. (2012) and Zeller (1994).

The coefficient on household size is significantly positive and robust in all regressions. This implies that households with more members are more likely to use MFI credit compared to those with fewer members. This result differs from study findings by Li et al. (2011), Mpuga

(2010) and Manrique and Ojah (2004) who found a significant but negative relationship between household size and household access to credit. These findings are supported by the fact that the larger the household, the higher the rate of time preference and therefore the higher the value of consumption in each period of time compared to a smaller household size.

4.5.2.3 Results Based on FinAccess 2015 by Poverty Status

Table 10 presents results for IV probit estimates obtained using 2015 data. Chi square statistics show that all the regressions are statistically significant. Exogeneity tests justify the use of instrumental variable estimators. Most of the coefficients on the explanatory variables are statistically significant and have expected signs. Robustness of the results in Table 9 is evaluated against IV 2SLS results, which are provided in Appendix Table A13.

Table 10: IV Probit estimates of the probability of using MFI credit by poverty status (2015)

	Dependent variable: Dummy = 1 if ever used MFI loan, 0 otherwise					
	(a)	(b)	(c)	(d)	(e)	(f)
	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
M-money	-0.08	0.02				
	(0.113)	(0.121)				
M-banking			-0.01	-0.19***		
			(0.136)	(0.066)		
M-Credit					-0.01	-0.19***
					(0.162)	(0.071)
Income	0.87***	0.83***	0.86***	0.83***	0.86***	0.83***
	(0.046)	(0.041)	(0.047)	(0.041)	(0.044)	(0.040)
Age	-5.97***	-0.30	-5.97***	-1.15	-6.12***	-1.31
	(1.914)	(1.877)	(2.171)	(2.024)	(2.060)	(2.026)
Age squared	0.88***	0.14	0.89***	0.25	0.90***	0.27
	(0.253)	(0.247)	(0.287)	(0.266)	(0.273)	(0.267)
Male	-0.47***	-0.37***	-0.48***	-0.35***	-0.48***	-0.36***
	(0.053)	(0.046)	(0.056)	(0.044)	(0.055)	(0.045)
Married	-0.25***	-0.09*	-0.26***	-0.09*	-0.26***	-0.09*
	(0.059)	(0.051)	(0.061)	(0.052)	(0.060)	(0.052)
Education	0.09	0.13	0.09	0.10	0.09	0.10
	(0.112)	(0.123)	(0.119)	(0.125)	(0.117)	(0.125)
HH Size	0.10*	0.11***	0.11**	0.11***	0.11**	0.12***
	(0.052)	(0.033)	(0.053)	(0.033)	(0.052)	(0.033)
Rural	0.05	0.18***	0.06	0.17***	0.06	0.17***
	(0.067)	(0.045)	(0.069)	(0.045)	(0.068)	(0.045)
No of obs.	2,756	4,935	2,756	4,935	2,756	4,935
Chi2	1474	1669	1371	1683	1398	1665
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Exogeneity test	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is usage of microcredit dummy. IV refers to instrumental variable. Robust standard errors are reported (in parentheses). ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. All regressions include a constant county dummies but these are not reported.

When the sample is split on the basis of poverty, the effect of M-money on the probability to borrow from an MFI remains insignificant among both poor and non-poor respondents. However, the effect of M-banking and M-credit on the probability to borrow from an MFI is negative and statistically significant among the non-poor but insignificant among the poor. Among the non-poor, the predicted probability of using MFI credit is on average around 7% higher for those who have ever used M-banking than for those who had never used M-banking (p<0.01). On average, a change from never using M-credit to using M-credit decreases the probability of using MFI credit by 5% among the non-poor ($p<0.05$). Two key conclusions can be drawn from these findings. First: the emergence of M-banking and M-credit in Kenya's finance sector seems to be displacing the uptake of microfinance services among non-poor households. Secondly, M-money, M-banking and M-credit have not been instrumental in helping poor households to access microfinance services. This is surprising since MFS have been touted to drive the empowerment of the poor.

Apart from mobile-based financial services, other factors that determine the propensity to use MFI credit among the poor include income, age, gender, marital status and household size. Among the non-poor, the factors that determine the propensity to use MFI credit include income, gender, marital status, household size and type of cluster (or location).

4.6 Conclusion and Policy Recommendations

Many studies belabour the wide differences in access to credit across individuals and households. Personal characteristics (such as age, gender, education, employment status, income and many others) plus household descriptors (such as family size, consumption, assets and poverty level among others) dominate the explanations as to why these disparities exist. Few studies analyse the role of MFS in determining access to credit. However, this investigation identifies the predictors of Kenyans' propensity to use MFI credit with a focus on the effects of M-money, M-banking and M-credit. It applies a discrete choice framework using 2013 (N=6449) and 2015 (N=8665) household data. Due to endogeneity concerns arising from reverse causality between borrowing and income, the study employed instrument variable estimators. This approach is validated by tests for endogeneity of income and instrument validity tests. The predictors of the propensity to use MFI credit in 2015 are M-banking, M-credit, income, age, gender, marital status, schooling, household size and cluster type. In 2013, the likelihood of using MFI credit is determined by income, gender and cluster type. In both 2013 and 2015, the effect of M-credit on the probability of borrowing from an MFI is negative but is not robust to the use of different estimators.

Four issues of concern stand out from the findings. Firstly, income is significantly associated with a higher propensity to use MFI credit. Had MFIs been serving the poor in line with their mission, the relationship would be negative. A positive sign implies that the non-poor are crowding out the poor from microfinance markets. The second key observation is that the sign on M-banking is negative and statistically significant, suggesting that the use of this service is dislocating the users away from the use of MFI credit. Given that some banks and MFIs have started to migrate towards M-banking platforms, this finding may be a pointer to the fact that these interventions are bearing fruit especially with the rising competition in the finance sector. Thirdly, the significantly negative relationship between using M-credit and the likelihood of using MFI credit implies that M-credit applications in Kenya are shifting customers away from MFIs. Fourthly, analysis of the data by poverty status reveals that the coefficients on M-banking and M-credit are negative and statistically significant among non-poor households but negative and insignificant among poor households. This suggests that the negative effects of M-banking and M-credit on the propensity to use MFI credit observed at the aggregate level are largely driven by the negative impacts of M-banking and M-credit on the likelihood of non-poor households to access microcredit. While it is evident that these financial innovations are helping the non-poor to shift away from MFI credit, the poor are being left out of these shifts. Ironically, these applications are widening the digital divide between the poor and non-poor in the microfinance sector yet they are expected to empower low-income households and close the existing gaps between the two groups.

In terms of policy, it is recommended that MFIs improve their client targeting process in order to focus their lending towards the poor. In part, they should target sectors with heavy concentrations of the poor and apply credit scoring approaches that recognize the characteristics of poorer clients. To enhance the role of M-credit in players in the MFI sector should explore partnerships with the developers of the M-credit apps. This will help to integrate MFI services and M-credit.

Chapter 5

Conclusion

In recent years, particularly since 2000, there has been a surge in lending by microfinance institutions in SSA. Since loan growth in microfinance is an indicator of poverty outreach and financial inclusion, there has been much excitement about "banking the poor" through microfinance. However, along with this excitement, there is heightened concern among practitioners, researchers and regulators following the rising loan delinquencies in the MFI sector. In fact, many MFIs have either collapsed or have been declared insolvent. These outcomes threaten the stability and financial health of these institutions. Unfortunately, little is known on how loan growth, especially when it is excessive, affects credit risk in SSA MFIs as well as the drivers of both credit risk and loan growth in SSA microfinance markets. In addition, research is yet to establish the effect of MFS on access to microfinance.

With this background in mind, this thesis is motivated by the remarkable loan growth and the rising credit risk that MFIs experienced as well as by the fact that SSA has been neglected in the relevant literature. The thesis has contributed to knowledge in several ways. First, it has provided evidence from SSA on the predictors of MFIs' loan growth (Chapter two) and credit risk (Chapter three). Second, it has provided evidence on the factors that determine access to MFIs credit (Chapter four) by paying particular attention to the effects of MFS, an aspect that was ignored in previous studies. Finally, the thesis has overcome the limitations of previous studies that employed static regressions (which are limited in dealing with panel endogeneity bias) by paying particular attention to dynamic aspects of loan growth and credit risk.

Chapters two and three, which approached microfinance from the supply-side, considered the lending behaviour in MFIs and whether excessive lending was associated with higher risk exposure. Specifically, the two Chapters examined the predictors of loan growth and credit risk, respectively. The two Chapters also provided international comparisons, which was useful as it allowed the evaluation of whether factors that turned out significant in SSA were also important elsewhere. To achieve these objectives, the two Chapters applied system generalised method of moments estimators on data from 37 SSA countries covering the period from 2004 to 2014. This data was assembled from four sources – MIX dataset, World Development Indicators, World Governance Indicators and Doing Business Indicators. Chapter four, which approached microfinance from the demand-side, examined some of the potential barriers to accessing MFI credit at the household level in Kenya but paid particular attention to the role of MFS. Chapter four applied instrumental variable discrete models on FinAccess data sets (2013 and 2016) and accommodated endogeneity in the models. Unlike Chapters two and three, Chapter four focused on Kenya because the country out-performs other Sub-Sahara African countries in terms of financial and digital inclusion, which has been attributed to the explosion in the M-PESA (mobile money) financial innovation that has drastically altered the way people save, borrow and transact.

Evidence in Chapters two and three supports the existence of trade-offs between loan growth and risk. This implies that those MFIs that recorded higher loan growth were facing lower risk exposure and vice versa. In addition, Chapter three established the existence of threshold effects in the relationship between credit risk and loan growth, which suggests that excessive loan growth is harmful to the stability and financial health of the MFIs. In fact, credit risk fell with loan growth until a trough at 36% when this relationship was reversed. Analyses in Chapters two and three revealed that dynamics were important in predicting both loan growth and risk indicating that these two variables were persistent and some divergence mechanism was at play. In other words, MFIs that recorded higher loan growth (or risk) in one year were more likely to record higher loan growth (or risk) in the following year. Further evidence in Chapter two showed that loan growth was higher in MFIs that were having higher capital-asset ratios, in countries that were having better economic prospects and in those countries with sound private sector policies and regulations. Against expectations, loan growth was faster in countries that were having poor legal rights of borrowers and lenders. This was attributed to the fact that the legal reforms that sought to promote the rights of borrowers and lenders may have made it costlier for MFIs to increase lending in a fully compliant way.

In Chapter three, credit risk was found to be higher in MFIs that made high provisions for loan impairment, which was unexpected because the conventional use of these provisions for loan impairment is by regulators to internalize credit risk. Therefore, the positive relationship between credit risk and provisions for loan defaults should worry prudential regulators of MFIs. The Chapter also established a negative relationship between credit risk and GDP per capita growth, which showed that higher incomes in the economy were associated with lower default risk. MFIs that were located in countries with ease of getting credit tended to suffer from high loan default rates as a result of the exposure of MFIs to moral hazard and adverse selection problems.

One of the objectives of Chapters two and three was to establish whether the factors that turned out significant in SSA regressions remained statistically significant in the regressions for EAP, EECA, LAC and SA. Regarding loan growth (Chapter two), three factors were statistically significant across all regions: lagged loan growth, credit risk and regulatory quality. However, the coefficients on these factors varied across all the regions, implying that the impacts were heterogenous. In addition to the three factors that were statistically significant across all regions, three other factors were statistically significant in four out of the five regions. These three factors were capital asset ratio (was statistically significant in SSA, EAP, EECA and LA), money supply (was statistically significant in EAP, EECA, LA and SA) and GDP growth (was statistically significant in SSA, EAP, EECA and LA). Regarding credit risk (Chapter three), the factors that were statistically significant across all regions included lagged credit risk, loan growth and provision for loan impairment. Loan growth squared was statistically significant in SSA, EAP, LAC and SA but statistically insignificant in EECA. Given these findings in Chapters two and three, it was concluded that both micro-level and macro-institutional factors influences the performance of MFIs. However, the effects of different factors are heterogenous across different regions.

Another important aspect in the area of microfinance is the role of mobile financial services, given that not many studies have examined this role. Chapter four examined the factors that explain differences in the usage of MFI credit in Kenya but paid particular attention to the effect of mobile financial services on the usage of MFI credit. The results showed that the probability that an individual used MFI credit was lower among those individuals that used M-banking and M-credit. These results suggest that M-Money and M-credit, on one hand, and MFI credit, on the other hand, are substitutes. This finding is explained by the convenience in terms of lower transaction costs, fast speed and fewer distance barriers that are associated with M-Money and M-credit compared to MFI credit. The likelihood of using MFI credit is also lower among males and married persons. The focus of microcredit on women rather than on men has been attributed to the fact that women are more likely to be poor but better credit risks compared to men (D’espallier et al., 2011; Ledgerwood, 1999). Conversely, income, education, household size and location in a rural cluster were associated with a higher propensity to use MFI credit. Given that the mission of MFIs is to provide loans to the poor, the positive and significant effect of income on access to MFI credit should be of concern. It may suggest that microfinance is serving the needs of the non-poor at the expense of the poor who should be the main beneficiaries. Non-linearities were detected in the relationship between the probability of using MFI credit and age of the prospective borrower.

The findings in this thesis have important implications for researchers, practitioners and regulators of MFIs in SSA. First, the confirmation of threshold effects in the relationship between loan growth and risk implies that modest loan growth was not a source of instability in the MFI sector. However, excessive loan growth was detrimental to the stability and financial health of MFIs. This implies that prudent management of credit risk in MFIs will require a deliberate effort on the part of MFIs to determine the threshold beyond which loan growth becomes detrimental to their stability. Second, dynamics have been shown to predict lending growth and credit risk. This implies that lending methodologies (credit scoring, credit modelling) that incorporate past lending and loan defaults are likely to perform better. Third, the predictors of credit risk and loan growth in SSA are not necessarily the same in other regions. This implies that the regions are heterogenous and any policy interventions directed at managing loan growth and credit risk in MFIs should necessarily be heterogenous. In other words, the “one-size-fits-all” type of interventions may not work in microfinance. Fourth, the fact that both MFI-level, macroeconomic and institutional factors were found to significantly determine the levels of credit risk and loan growth implies that policies that promote MFIs should be necessarily complemented by favourable macroeconomic policies and a conducive regulatory and political environment. Fifth, the finding that income is positively associated with the usage of MFI credit implies that the non-poor are “crowding-out” the poor from microfinance markets. In terms of policy, MFIs should improve their client targeting process in order to focus their lending towards the poor. In part, they should target sectors with heavy concentrations of the poor and apply credit scoring approaches that recognize the characteristics of poorer clients. Lastly, the substitutability between M-banking and M-credit on one hand, and MFI credit, on the other hand, suggests that there is need to enhance the role of M-credit in the MFI sector via building partnerships with developers of M-credit apps. The developers of the apps could then develop systems that integrate the features of MFI credit into their apps.

In terms of research limitations, there were many outliers in the Mixmarket datasets that were used in Chapters two and three of this thesis although log-transformations were combined with instrumental variable estimators to minimize the impact of such outliers on the regression estimates. The presence of outliers was evident from huge disparities between the means and medians. In addition, the two chapters attempted to examine trade-offs between loan growth and credit risk using system GMM estimators based on mean regressions. However, mean regressions are limited in identifying trade-offs at different points in the conditional distribution of loan growth and credit risk. Further research in this area should explore the possibility of using quantile regression approach, which is based on median regression and is able to examine the impact of loan growth on credit risk (and vice versa) on both the location and the scale of parameters of the model. A quantile regression has the extra merit of being able to permit a richer understanding of the data and minimizes the impact of outliers on the regression results.

In Chapter 4, cross-sectional data for 2013 and 2015 were used since the two data sets could not be conveniently merged. Future research using FinAccess datasets in Kenya should explore the possibility of applying panel data sets. One of the main advantages of panel datasets is the feasibility of analysing dynamics as well as being able to control for individual heterogeneity and time-effects.

References

Abedifar, P., Molyneux, P., & Tarazi, A. (2013). Risk in Islamic banking. *Review of Finance*, *17*(6), 2035-2096.

Abid, L., Ouertani M. N., & Zouari-Ghorbel, S. (2014) Macroeconomic and bank-specific determinants of household's non-performing loans in Tunisia: A dynamic panel data. *Procedia Economics and Finance, 13*, 58-68.

Ahlin, C., Lin, J., & Maio, M. (2011). Where does microfinance flourish? Microfinance institution performance in macroeconomic context. *Journal of Development Economics*, *95*(2), 105-120.

Aisen, M. A., & Franken, M. (2010). *Bank credit during the 2008 financial crisis: A cross-country comparison* (No. 10-47). International Monetary Fund.

Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *The Journal of Economic Perspectives*, *24*(3), 207-232.

Akoten, J. E., Sawada, Y., & Otsuka, K. (2006). The determinants of credit access and its impacts on micro and small enterprises: The case of garment producers in Kenya. *Economic development and cultural change*, *54*(4), 927-944.

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, *5*(4), 393-409.

Ali, A., & Daly, K. (2010). Macroeconomic determinants of credit risk: Recent evidence from a cross country study. *International Review of Financial Analysis*, *19*(3), 165-171.

AMFI. (2014). Annual Report on the Microfinance Sector in Kenya, Association of Microfinance Institutions. Accessed at http://www.microfinanzarating.com/index.php on 22 November 2017

Amidu, M. (2014). What Influences Banks Lending in Sub-Saharan Africa?. *Journal of Emerging Market Finance*, *13*(1), 1-42.

Amri, P. D., Prabha, A. P., & Wihlborg, C. (2012). What Makes High Credit Growth Harmful? Evidence from Banking Crises. Available at SSRN: http://ssrn.com.

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American statistical Association*, *76*(375), 598-606.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Armendariz, B. and Morduch, J. (2010). *The economics of microfinance*. MIT Press.

Asghar, A., & Daly, K. (2010) Macroeconomic determinants of credit risk: Recent evidence from a cross country study. *International Review of Financial Analysis*, 19.3, 165-171.

Asongu, S. A. (2013). African stock market performance dynamics: a multidimensional convergence assessment. *Journal of African Business*, *14*(3), 186-201.

Asongu, S. A., & Nwachukwu, J. C. (2016). Revolution empirics: predicting the Arab Spring. *Empirical Economics*, *51*(2), 439-482.

Atieno, R. (1997). Determinants of credit demand by smallholder farmers in Kenya: An empirical analysis. *Der Tropenlandwirt – Journal of Agriculture in the Tropics and Subtropics*, *98*(1), 63-71.

Avdjiev, S., McCauley, R. N., & McGuire, P. (2012). Rapid credit growth and international credit: challenges for Asia. BIS Working Papers, no 377, April.

Baele, L., Farooq, M., & Ongena, S. (2010). Of Religion and Redemption: Evidence from Default on Islamic Loans (Replaced by CentER DP 2012-014). *CentER Discussion Paper*, *2010*.

Baker, M., & Wurgler, J. (2002). Market timing and capital structure. *The journal of finance*, *57*(1), 1-32.

Bakker, B. B., & Gulde, A. M. (2010). The credit boom in the EU new member states: bad luck or bad policies? IMF Working Paper 10/130.

Barajas, A., Dell'Ariccia, G., & Levchenko, A. (2007). Credit booms: The good, the bad, and the ugly. mimeo, IMF, Washington

Barslund, M., & Tarp, F. (2008). Formal and informal rural credit in four provinces of Vietnam. *The Journal of Development Studies*, *44*(4), 485-503.

Baselga-Pascual, L., Trujillo-Ponce, A., & Cardone-Riportella, C. (2015). Factors influencing bank risk in Europe: Evidence from the financial crisis. *The North American Journal of Economics and Finance*, *34*, 138-166.

Beegle, K., Christiaensen, L., Dabalen, A., & Gaddis, I. (2016). *Poverty in a rising Africa*. World Bank Publications.

Berger, A. N., & Udell, G. F. (2004). The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of financial intermediation*, *13*(4), 458-495.

Bernanke, B., Gertler, M., & Gilchrist, S. (1994). *The financial accelerator and the flight to quality* (No. w4789). National Bureau of Economic Research.

Bhanot, D., Bapat, V., & Bera, S. (2012). Studying financial inclusion in north-east India. *International Journal of Bank Marketing*, *30*(6), 465-484.

Bikker, J. A., & Hu, H. (2002). Cyclical patterns in profits, provisioning and lending of banks (DNB Staff Reports 86).

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115-143.

Boateng, F. G., Nortey, S., Asamanin Barnie, J., Dwumah, P., Acheampong, M., & Ackom-Sampene, E. (2016). Collapsing Microfinance Institutions in Ghana: An Account of How Four Expanded and Imploded in the Ashanti Region. *International Journal of African Development*, *3*(2), 5.

Boudriga, A., Taktak, N.B., & Jellouli, S. (2010). Bank specific, business and institutional environment determinants of banks nonperforming loans: evidence from MENA countries. *Economic Research Forum, Working Paper*, No. 547.

Bouvatier, V., & Lepetit, L. (2008) Banks' procyclical behavior: Does provisioning matter?.*Journal of international financial markets, institutions and money* 18, no. 5, 513-526.

Bouvatier, V., & Lepetit, L. (2012). Effects of loan loss provisions on growth in bank lending: some international comparisons. *International Economics*, *132*, 91-116.

Brzoza-Brzezina, M. (2005). Lending booms in the new EU Member States: will euro adoption matter? European Central Bank Working Paper No. 543.

Breuer, J.B. (2006). Problem bank loans, conflicts of interest, and institutions. *Journal of financial stability, 2*(3), 266-285.

Business, D. (2017). Equal Opportunity for All. *URL: doingbusiness. org/~/media/WBG/DoingBusiness/Documents/Annualeports/English/DB17-Full-Report.pdf*

Calza, A., Gartner, C., & Sousa, J. (2003). Modelling the demand for loans to the private sector in the euro area. *Applied economics*, *35*(1), 107-117.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics using stata* (Vol. 2). College Station, TX: Stata press.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge University Press.

Campbell, J. Y. (2006). Household finance. *The journal of finance*, *61*(4), 1553-1604.

Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling*, *31*, 672-683.

Chaibi, H., & Ftiti, Z. (2015). Credit risk determinants: Evidence from a cross-country study. *Research in international business and finance, 33*, 1-16.

Chen, G., Rasmussen, S., & Reille, X. (2010). Growth and vulnerabilities in microfinance. *Focus Note*, *61*(1), 1-21.

Cheng, E. (2007). The demand for microcredit as a determinant for microfinance outreach-evidence from China. *Savings and Development*, 307-334.

Chikalipah, S. (2018). Credit risk in microfinance industry: Evidence from sub-Saharan Africa. *Review of Development Finance*. 8, 38 – 48.

Churchill, C., & Coster, D. (2001). *Microfinance Risk Management Handbook*. Atlanta, GA: Economic Development Unit, CARE.

Cihak, M., & Hesse, H. (2010). Islamic banks and financial stability: An empirical analysis. *Journal of Financial Services Research, 38*(2-3), 95-113.

Crabb, P.R. & Keller, T. (2006). A test of portfolio risk in microfinance institutions. *Faith & economics*, *47*(48), .25-39.

Clair, R. T. (1992). Loan growth and loan quality: some preliminary evidence from Texas banks. *Economic Review-Federal Reserve Bank of Dallas*, 9.

Coricelli, F., Mucci, F., & Revoltella, D. (2006). Household credit in the New Europe: lending boom or sustainable growth? CEPR Discussion Papers No. 5520

Cottarelli, C., Dell'Ariccia, G., & Vladkova-Hollar, I. (2005). Early birds, late risers, and sleeping beauties: Bank credit growth to the private sector in Central and Eastern Europe and in the Balkans. *Journal of banking & Finance*, *29*(1), 83-104.

Cordella, A. (2006). Transaction costs and information systems: does IT add up?.*Journal of information technology*, *21*(3), 195-202.

Crabb, P. R., & Keller, T. (2006). A test of portfolio risk in microfinance institutions. *Faith & economics*, *47*.(48), 25-39.

Crook, J. (2001). The demand for household debt in the USA: evidence from the 1995 Survey of Consumer Finance. *Applied Financial Economics*, *11*(1), 83-91.

Das, A., & Ghosh S. (2007). Determinants of credit risk in Indian state-owned banks: An empirical investigation. *Economic Issues, 12*(2), 27.

Deaton, A. (2012). Franco Modigliani e la teoria del ciclo vitale del consumo (Franco Modigliani and the life-cycle theory of consumption). *Moneta e Credito, 58*(230).

Dell'Ariccia, G., Igan, D., & Laeven, L. U. (2012). Credit booms and lending standards: Evidence from the subprime mortgage market. *Journal of Money, Credit and Banking*, *44*(2-3), 367-384.

D'espallier, B., Guérin, I., & Mersland, R. (2011). Women and repayment in microfinance: A global analysis. *World Development*, *39*(5), 758-772.

Diagne, A. (1999). Determinants of household access to and participation in formal and informal credit markets in Malawi. Food Consumption and Nutrition Division Discussion Paper 67. International Food Policy Research Institute, Washington, D.C.

Dichter, T. (2007). A Second Look at Microfinance: The Sequence of Growth and Credit in Economic History: Development Policy Briefing Paper No 1. Cato Institute, Washington.

Djankov, S., McLiesh, C., & Shleifer, A. (2007). Private credit in 129 countries. *Journal of financial Economics*, *84*(2), 299-329.

Donner, J., & Tellez, C. A. (2008). Mobile banking and economic development: Linking adoption, impact, and use. *Asian journal of communication*, *18*(4), 318-332.

Dutta, D., & Magableh, I. (2006). A socio-economic study of the borrowing process: the case of microentrepreneurs in Jordan. *Applied Economics, 38*(14), 1627-1640.

Duy, V. Q., D'Haese, M., Lemba, J., & D'Haese, L. (2012). Determinants of household access to formal credit in the rural areas of the Mekong Delta, Vietnam. *African and Asian studies*, *11*(3), 261-287.

Elekdag, S., & Wu, M. Y. (2011). *Rapid Credit Growth: Boon or Boom-Bust?,* Working Paper no. 11/241, International Monetary Fund.

El-Gamal, M. A., & Inanoglu, H. (2005). Inefficiency and heterogeneity in Turkish banking: 1990–2000. *Journal of Applied Econometrics*, *20*(5), 641-664.

Farazi, S. (2014). Informal firms and financial inclusion: status and determinants. *Journal of International Commerce, Economics and Policy*, *5*(03), 1440011.

Fase, M. M. (1995). The demand for commercial bank loans and the lending rate. *European Economic Review*, *39*(1), 99-115.

Fernando, J. L. (2006). *Microfinance: Perils and prospects*, New York: Routlidge.

Festić, M., Kavkler A., & Repina, S. (2011). The macroeconomic sources of systemic risk in the banking sectors of five new EU member states. *Journal of Banking & Finance, 35*(2), 310-322.

Fofack, H. L. (2005). *Nonperforming loans in Sub-Saharan Africa: causal analysis and macroeconomic implications*. The World Bank. World Bank Policy Research Working Paper 3769.

Foos, D., Norden L., & Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance, 34*(12), 2929-2940.

Freixas, X., & Rochet, J. C. (2008). *Microeconomics of banking*. MIT press.

Fung, M. K. (2009). Financial development and economic growth: convergence or divergence?. *Journal of International Money and Finance*, *28*(1), 56-67.

Gambacorta, L., & Mistrulli, P. E. (2004). Does bank capital affect lending behavior? *Journal of Financial intermediation*, *13*(4), 436-457.

GOK. (2007). Kenya Integrated Budget Household Survey 2005/6: Vol. 1 – Basic Report, Kenya National Bureau of Statistics, Government of Kenya, Nairobi.

Gonzalez, A., (2007). Resilience of microfinance institutions to national macroeconomic events: An econometric analysis of MFI asset quality. MIX Discussion Paper No. 1. July.

Gonzalez, A. (2010). Is microfinance growing too fast? Microfinance Information Exchange, Mix Data Brief no. 5.

Graham, J. R. (2000). How big are the tax benefits of debt? *The Journal of Finance*, *55*(5), 1901-1941.

Hermes, N., Lensink, R. & Meesters, A. (2011). Outreach and efficiency of microfinance institutions. *World development*, *39*(6), pp.938-948.

Hofmann, B. (2004). The determinants of bank credit in industrialized countries: do property prices matter? *International finance*, *7*(2), 203-234.

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, 1371-1395.

Indicators, Worldwide Governance. (2015) The World Bank Group.

Jagun, A., Heeks, R., & Whalley, J. L. (2008). The impact of mobile telephony on developing country micro-enterprises: a Nigerian case study. *Information technology and international development*, *4*(4), 47-65.

Jensen, M.C., & Meckling, W.H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305-360.

Johnson, S., & Nino-Zarazua, M. (2009). Financial exclusion in Kenya and Uganda. Bath papers in international development, Working Paper No 1. Bath, UK: Centre for Development Studies.

Joshi, M. G. (2005). *Access to credit by hawkers: what is missing? Theory and evidence from India* (Doctoral dissertation, The Ohio State University).

Kauffman, R. J., & Riggins, F. J. (2010). Research directions on the role and impact of ICT in microfinance. *System Sciences (HICSS), 2010 43rd Hawaii International Conference*, 1-10.

Kauko, K. (2012). External deficits and non-performing loans in the recent financial crisis. *Economics Letters, 115*(2), 196-199.

Keeton, W. R. (1999). Does faster loan growth lead to higher loan losses? *Economic Review-Federal Reserve Bank Of Kansas City*, *84*(2), 57.

Khoi, P. D., Gan, C., Nartea, G. V., & Cohen, D. A. (2013). Formal and informal rural credit in the Mekong River Delta of Vietnam: Interaction and accessibility. *Journal of Asian Economics*, *26*, 1-13.

Kimuyu, P., & Omiti, J. (2000). Institutional impediments to access to credit by micro and small scale enterprises in Kenya. Discussion Paper No 26. Nairobi: Institute of Policy Analysis and Research.

Kiss, G., Nagy, M., & Vonnák, B. (2006, June). Credit growth in Central and Eastern Europe: Trend, cycle or boom. In *conference "Finance and Consumption Workshop: Consumption and Credit in Countries with Developing Credit Markets", Florence* (pp. 16-17).

Kochar, A. (1997). An empirical investigation of rationing constraints in rural credit markets in India. *Journal of Development Economics*, *53*(2), 339-371.

Krauss, N., & Walter, I. (2009). Can microfinance reduce portfolio volatility?. *Economic Development and Cultural Change*, *58*(1), 85-110.

Laidroo, L., & Kadri, M. (2014). Perils of excessive credit growth: evidence from 11 new EU member states. *Baltic Journal of Economics, 14*(1-2), 17-34.

Lane, P. R., & McQuade, P. (2014). Domestic credit growth and international capital flows. *The Scandinavian Journal of Economics*, *116*(1), 218-252.

Lassoued, N. (2017). What drives credit risk of microfinance institutions? International evidence. *International Journal of Managerial Finance*, *13*(5), 541-559.

Ledgerwood, J. (1999). *Sustainable banking with the poor: microfinance handbook*. World Bank, Washington D.C.

Li, X., Gan, C., & Hu, B. (2011). Accessibility to microcredit by Chinese rural households. *Journal of Asian Economics, 22*(3), 235-246.

Louzis, D.P.,Vouldis, A.T., & Metaxas V.L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance, 36*(4), 1012-1027.

Love, I., & Ariss, R. T. (2014). Macro-financial linkages in Egypt: A panel analysis of economic shocks and loan portfolio quality. *Journal of international financial markets, institutions and money*, *28*, 158-181.

Lützenkirchen, C., Weistroffer, C., Speyer, B., & AG, D. B. (2012). Microfinance in evolution. An industry between crisis and advancement, Deutsche Bank Research, September, 13.

Majid, A., & Rais, A. (2003, March). Development of liquidity management instruments: challenges and opportunities. In *International Conference on Islamic Banking: Risk Management, Regulation and Supervision, held in Jakarta Indonesia September*.

Manrique, J., & Ojah, K. (2004). Credits and non-interest rate determinants of loan demand: a Spanish case study. *Applied Economics*, *36*(8), 781-791.

Marcucci, J., & Quagliariello, M. (2009). Asymmetric effects of the business cycle on bank credit risk. *Journal of Banking & Finance*, *33*(9), 1624-1635.

Marulanda, B., Fajury, L., Paredes, M., & Gomez, F. (2010). Taking the good from the bad in microfinance: lessons learned from failed experiences in Latin America. report written for Calmeadow, http://www. calmeadow. com/pdf/failures. pdf [Date last accessed: 14 February 2014].

Mbiti, I., & Weil, D. N. (2011). Mobile banking: The impact of M-Pesa in Kenya (No. w17129). *National Bureau of Economic Research*.

McMullen, J. S., Bagby, D., & Palich, L. E. (2008). Economic freedom and the motivation to engage in entrepreneurial action. *Entrepreneurship Theory and Practice*, *32*(5), 875-895.

Mendoza, E. G., & Terrones, M. E. (2008). *An anatomy of credit booms: evidence from macro aggregates and micro data* (No. w14049). National Bureau of Economic Research.

Mishkin, F. S. (2013). *The economics of money, banking, and financial markets*. Pearson education.

Mohamad, S., Hassan, T., & Bader, M. K. I. (2008). Efficiency of conventional versus Islamic Banks: international evidence using the Stochastic Frontier Approach (SFA). *Journal of Islamic Economics, Banking and Finance*, *4*(2), 107-130.

Mohieldin, M. S., & Wright, P. W. (2000). Formal and informal credit markets in Egypt. *Economic development and cultural change*, *48*(3), 657-670.

Moyi, Eliud Dismas. "Credit and employment growth among small enterprises in Kenya." *International Journal of Business and Economics Research* 2, no. 3 (2013): 69-76.

Mpofu, T. and Nikolaidou, E. (2018) The Determinants of Credit Risk in the Banking Systems in Sub-Saharan Africa. *Review of Development Finance*, (available on line at: https://www.sciencedirect.com/science/article/pii/S1879933718300368, August 2018)

Mpuga, P. (2010). Constraints in access to and demand for rural credit: Evidence from Uganda. *African Development Review*, *22*(1), 115-148.

Myers, S. C. (1984). The capital structure puzzle. *The journal of finance*, *39*(3), 574-592.

Nguyen, C. H. (2007). Determinants of credit participation and its impact on household consumption: Evidence from rural Vietnam. CERT Discussion Papers 0703, Centre for Economic Reform and Transformation, Heriot Watt University.

Njoroge, L., & Kamau, A. W. (2010). Macroeconomic Developments and Banks' Behaviour in Kenya: A Panel Data Analysis. *Savings and Development*, 191-217.

North, D. C. (1990). Institutions and a transaction-cost theory of exchange. *Perspectives on positive political economy*, *182*, 191.

Noomen, N., & Abbes, M. B. (2018). The Determinants of Credit Risk Management of Islamic Microfinance Institutions. *IUP Journal of Financial Risk Management*, *15*(1).

Okurut, F. N. (2006). Access to credit by the poor in South Africa: Evidence from Household Survey Data 1995 and 2000. Working Paper No 13, Department of Economics, University of Stellenbosch, South Africa.

Okurut, F.N., Schoombee, A. and Berg, S., 2005. Credit demand and credit rationing in the informal financial sector in Uganda. *South African Journal of Economics*, *73*(3), 482-497.

Onyuma, S. O., & Shem, A. O. (2005). Myths of microfinance as a panacea for poverty eradication and women empowerment. *Savings and Development*, 199-222.

Pal, S. (2002). Household sectoral choice and effective demand for rural credit in India. *Applied Economics*, *34*(14), 1743-1755.

Park, S. (1994). Explanations for the increased riskiness of banks in the 1980s. *Federal Reserve Bank of St. Louis Review*, *76*(4), 3.

Parker, S. C. (2018). *The economics of entrepreneurship*. Cambridge University Press.

Pesola, J. (2011). Joint effect of financial fragility and macroeconomic shocks on bank loan losses: Evidence from Europe. *Journal of Banking & Finance*, *35*(11), 3134-3144.

Plosser, C. I. (1989). Understanding real business cycles. *The Journal of Economic Perspectives*, *3*(3), 51-77.

Quagliariello, M. (2007). Banks' riskiness over the business cycle: a panel analysis on Italian intermediaries. *Applied Financial Economics*, *17*(2), 119-138.

Quiggin, J. (1999). Human capital theory and education policy in Australia. *Australian Economic Review*, *32*(2), 130-144.

Riquet, C., & Poursat, C. (2013). Managing Failing Deposit Taking Institutions: Regulatory Experience from Africa. Focus Note 91. Washington, D.C.: CGAP.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, *9* (1), 86-136.

Sainz-Fernandez, I., Torre-Olmo, B., López-Gutiérrez, C., & Sanfilippo-Azofra, S. (2015). Crisis in microfinance institutions: Identifying problems. *Journal of International Development*, *27*(7), 1058-1073.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research, 22*(3), 203-224.

Samad, A., & Hassan, M. K. (1999). The performance of Malaysian Islamic bank during 1984-1997: An exploratory study. *International journal of Islamic financial services*, *1*(3), 1-14.

Schmit, M., & Marrez, H. (2010). Credit risk in microcredit: how does gender matter? *Savings and Development*, 369-388.

Shankar, S., & Asher, M. G. (2010). Regulating microfinance: A suggested framework. *Economic and Political Weekly*, 15-18.

Shem, A. O., Misati, R., & Njoroge, L. (2012). Factors driving usage of financial services from different financial access strands in Kenya. *Savings and Development*, *36*(1), 71-89.

Shleifer, A., & Vishny, R. W. (1989). Management entrenchment: The case of manager-specific investments. *Journal of financial economics*, *25*(1), 123-139.

Simoes, N., Crespo, N., & Moreira, S. B. (2016). Individual determinants of self-employment entry: What do we really know? *Journal of economic surveys*, *30*(4), 783-806.

Sinkey, J. F., & Greenawalt, M. B. (1991). Loan-loss experience and risk-taking behavior at large commercial banks. *Journal of Financial Services Research*, *5*(1), 43-59.

Steiner, S., Giesbert, L., & Bendig, M. (2009). Savings, credit and insurance: household demand for formal financial services in rural Ghana. GIGA Working Papers, No. 94, German Institute of Global and Area Studies (GIGA), Hamburg.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, *71*(3), 393-410.

Swain, R. B. (2007). The demand and supply of credit for households. *Applied Economics*, *39*(21), 2681-2692.

Taniguchi, H. (2002). Determinants of women's entry into self–employment. *Social Science Quarterly*, *83*(3), 875-893.

Triki, T., & Faye, I. (2013). Financial inclusion in Africa. Tunis, *African Development Bank.*

Turvey, C. G., & Kong, R. (2010). Informal lending amongst friends and relatives: can microcredit compete in rural China?. *China Economic Review*, *21*(4), 544-556.

Udry, C. (1990). Credit markets in Northern Nigeria: Credit as insurance in a rural economy. *The World Bank Economic Review*, *4*(3), 251-269.

Villasenor, J. D., West, D. M., & Lewis, R. J. (2016). The 2016 Brookings financial and digital inclusion project report: Advancing equitable financial ecosystems. Washington, DC: Center for Technology Innovation at Brookings.

Vithessonthi, C. (2016). Deflation, bank credit growth, and non-performing loans: Evidence from Japan. *International Review of Financial Analysis*, *45*, 295-305.

Wagner, C., & Winkler, A. (2013). The vulnerability of microfinance to financial turmoil–evidence from the global financial crisis. *World Development*, *51*, 71-90.

Wald, J. K. (1999). How firm characteristics affect capital structure: an international comparison. *Journal of Financial research*, *22*(2), 161-187.

Weber, D., Kulkarni, U., & Riggins, F. (2012). Breadth and Depth: The impact of ICT Adoption on Outreach Capabilities of Microfinance Institutions. *AMCIS 2012 Proceedings*. Paper 2.

Wichterich, C. (2012). The Other Financial Crisis: Growth and crash of the microfinance sector in India. *Development*, *55*(3), 406-412.

Wooldridge, J. M. (2013). *Introductory econometrics: A modern approach*. Nelson Education.

Wu, D., & Wu, Z. (2015). Intergenerational links, gender differences, and determinants of self-employment. *Journal of Economic Studies*, *42*(3), 400-414.

Yimga, J. (2016). The impact of high microfinance growth on loan portfolio. *Journal of International Development*, *28*(5), 697-714.

Zeller, M. (1994). Determinants of credit rationing: A study of informal lenders and formal credit groups in Madagascar. *World development*, *22*(12), 1895-1907.

Appendix

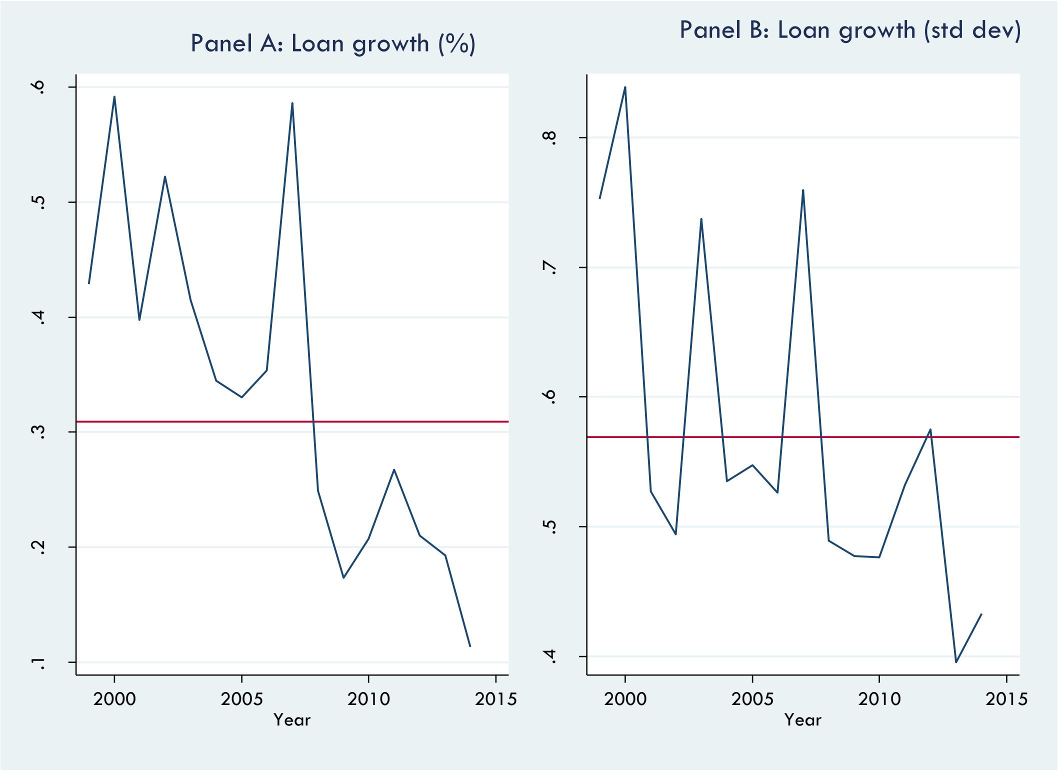

Figure A1: Gross loan portfolio - growth and variability

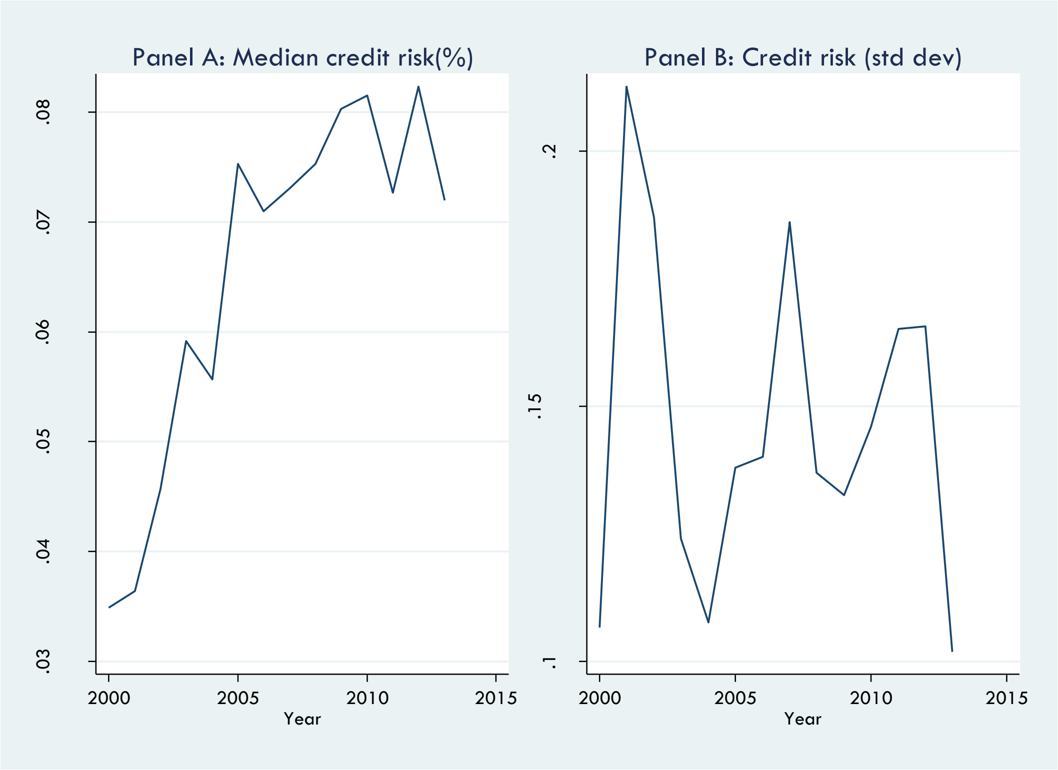

Figure A2: Credit risk and it's variability

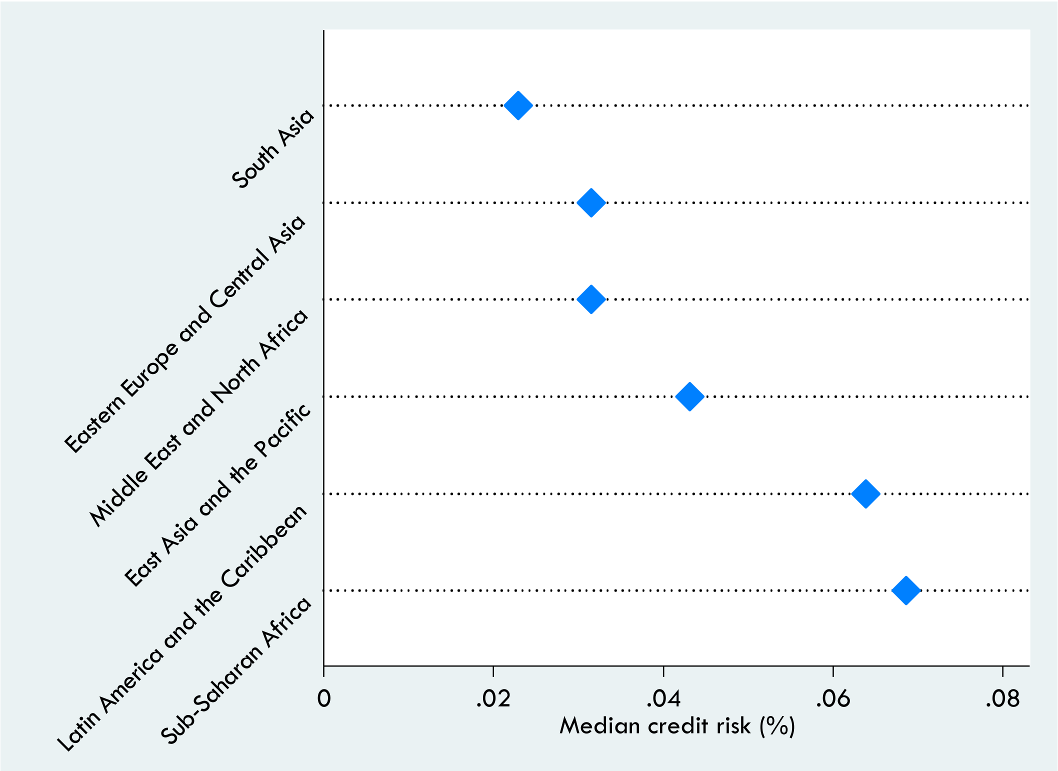

Figure A3: Global distribution of credit risk (2000-2014)

Table A1: Selected indicators of microfinance outreach

	2000	2014	Median annual growth (%) 2000-2014	2000-2007	2007-2014
Gross loan portfolio					
Central Africa	-	537	25.5	39.9	19.0
Eastern Africa	6.03	3150	28.2	38.2	19.5
Southern Africa	152	321	27.2	38.3	14.7
Western Africa	42.4	1860	23.3	34.5	15.5
Total	255	5870	25.0	36.8	16.7
Assets					
Central Africa	-	1020	26.2	40.8	18.9
Eastern Africa	129	5520	29.2	38.5	18.5
Southern Africa	178	470	28.5	35.2	19.8
Western Africa	5690	2910	21.1	38.4	12.4
All	364	9910	25.0	38.2	14.9
Number of active borrowers					
Central Africa	-	179798	18.8	29.2	11.1
Eastern Africa	409088	873,241	20.8	28.5	12.9
Southern Africa	36646	354,717	16.6	21.4	12.9
Western Africa	408958	2,919,658	17.3	19.4	16.2
All	854,692	4327414	18.0	24.5	14.4
Number of depositors					
Central Africa	-	784608	20.0	25.1	15.6
Eastern Africa	456101	4916107	25.5	31.1	19.9
Southern Africa	11865	1906107	25.4	37.7	18.4
Western Africa	304680	7175222	20.8	21.1	20.3
All	772646	14800000	22.7	25.2	15.5

Source: Own computations using (www.mixmarket.org) database. Gross loan portfolio and assets are measured in US$ millions

Table A2: A comparison of selected MFI indicators in SSA and Non-SSA (2000 – 2014)

	All		SSA		Non-SSA		
	Obs.	Mean	Obs.	Mean	Obs.	Mean	t-ratio
Institutional characteristics							
Offices	10610	44	1922	27	8688	47	4.25***
Loan officers	10943	206	2084	116	8859	227	4.41***
Outreach indicators							
Number of active borrowers (‘000)	15062	63	3139	23	11923	73	6.77***
Percent of women borrowers	12245	0.65	2402	0.60	9843	0.66	10.3***
Gross loan portfolio USD millions	16313	41.1	3676	31.5	12637	43.9	2.06**
Overall financial performance							
Operational self-sustainability	14745	1.17	3125	1.06	11620	1.20	5.77***
Revenues							
Financial revenue ratio	12326	0.27	2374	0.26	9952	0.27	2.19**
Yield on gross loan portfolio	10017	0.25	1621	0.28	8396	0.24	-6.42***
Expenses							
Total expense ratio	12338	0.26	2363	0.29	9975	0.26	-5.50***
Financial expense ratio	9715	0.10	1591	0.11	8124	0.10	-0.767
Loan loss provision expense ratio	11826	0.09	2127	0.31	9699	0.04	-2.62***
Administrative expense ratio	9874	0.08	1623	0.12	8251	0.08	-14.9***
Efficiency							
Operating expense/loan portfolio	12332	0.31	2329	0.47	10003	0.27	-14.6***
Personnel expense/loan portfolio	9744	0.15	1564	0.19	8180	0.14	-6.43***
Productivity							
Borrowers per staff member	10658	313	1947	346	8711	305	-3.69***
Depositors/staff member	12279	131	2599	244	9680	100	-19.3***
Risk and liquidity							
Write off rate	10950	0.03	1824	0.05	9126	0.02	-3.51***
Non-earning liquid assets/ total assets	11277	0.17	2071	0.23	9206	0.15	-22.8***

***significant at the 10% level, **significant at the 5% level, *significant at the 10% level
Source: Own computations using (www.mixmarket.org) database

Table A3: Sample countries

SSA	South Asia	MENA	LAC	EECA	ECA
Angola Benin Burkina Faso Burundi Cameroon Central African Republic Chad Comoros DRC Congo Cote d'Ivoire Ethiopia Gabon Gambia Ghana Guinea Guinea-Bissau Kenya Liberia Madagascar Malawi Mali Mozambique Namibia Niger Nigeria Rwanda Senegal Sierra Leone South Africa South Sudan Swaziland Tanzania Togo Uganda Zambia Zimbabwe	Afghanistan Bangladesh Bhutan India Nepal Pakistan Sri Lanka	Egypt Iraq Jordan Lebanon Morocco Palestine Sudan Syria Tunisia Yemen	Argentina Belize Bolivia Brazil Chile Colombia Costa Rica Dominican Republic Ecuador El Salvador Grenada Guatemala Guyana Haiti Honduras Jamaica Mexico Nicaragua Panama Paraguay Peru Saint Lucia Suriname Trinidad and Tobago Uruguay Venezuela	Albania Armenia Azerbaijan Bosnia and Herzegovina Bulgaria Croatia Georgia Hungary Kazakhstan Kosovo Kyrgyzstan Macedonia Moldova Mongolia Montenegro Poland Romania Russia Serbia Slovakia Tajikistan Turkey Ukraine Uzbekistan	Cambodia China East Timor Fiji Indonesia Laos Malaysia Myanmar (Burma) Papua New Guinea Philippines Samoa Solomon Islands Thailand Tonga Vanuatu Vietnam

Table A4: Cross-country specific variables (averages for 2004 – 2014)

	Loan growth (ratio)	Credit risk (Ratio)	Capital asset ratio	Return on equity	HHI-Index
Angola	0.383	0.066	0.427	0.185	0.109
Benin	0.203	0.125	0.149	0.785	0.022
Burkina Faso	0.261	0.074	0.225	0.065	0.080
Burundi	0.244	0.115	0.360	-0.193	0.057
Cameroon	0.239	0.173	0.227	-0.006	0.040
CAR	0.111	0.381	0.042	1.152	0.136
Chad	0.176	0.095	0.375	0.028	0.089
Comoros	-0.016	0.108	0.187	0.096	0.275
DRC	0.521	0.103	0.389	0.143	0.078
Congo	0.193	0.116	0.270	-0.019	0.293
Cote d'Ivoire	0.275	0.175	-0.211	0.812	0.078
Ethiopia	0.307	0.072	0.441	0.085	0.036
Gabon	0.522	0.172	0.735	-0.436	0.530
Gambia	0.510	0.180	0.299	-0.386	0.105
Ghana	0.272	0.105	0.268	0.1745	0.117
Guinea	0.399	0.093	0.288	0.078	0.056
Guinea-Bissau	0.873	1.148	0.090	-2.017	0.268
Kenya	0.363	0.104	0.357	-0.362	0.062
Liberia	0.208	0.190	0.559	-0.209	0.257
Madagascar	0.264	0.114	0.357	-0.121	0.020
Malawi	0.321	0.097	0.503	-0.372	0.084
Mali	0.272	0.089	0.279	0.100	0.021
Mozambique	0.236	0.075	0.519	-0.057	0.046
Namibia	0.491	0.023	0.325	-1.718	0.249
Niger	0.111	0.124	0.392	-0.074	0.055
Nigeria	0.352	0.141	0.419	0.238	0.033
Rwanda	0.277	0.269	0.446	-0.068	0.197
Senegal	0.149	0.093	0.160	-0.045	0.031
Sierra Leone	0.378	0.085	0.542	-0.097	0.053
South Africa	0.253	0.226	0.488	-0.350	0.188
South Sudan	0.286	0.213	0.265	0.227	0.272
Swaziland	0.164	0.112	0.398	0.048	0.111
Tanzania	0.268	0.080	0.330	0.017	0.116
Togo	0.201	0.171	0.117	-0.109	0.056
Uganda	0.314	0.098	0.345	0.108	0.060
Zambia	0.316	0.184	0.578	-0.388	0.042
Zimbabwe	-0.216	0.267	0.373	0.370	0.115
SSA	0.280	0.124	0.308	0.035	0.076

Note: DRC is Democratic Republic of Congo. Non-SSA refers to the following country groupings – East Asia and the Pacific (EAP), Eastern Europe and Central Asia (EECA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA) and South Asia (SA). Loan growth refers to growth in loan portfolio.

Table A5: Descriptive statistics

	Mean	Median	SD	Minimum	Maximum	Skewness	Kurtosis
Loan growth (ratio)	0.29	0.23	0.52	-2.54	5.31	2.63	26.27
Credit risk (ratio)	0.12	0.08	0.15	0.00	2.08	4.98	45.16
HHI (index)	0.06	0.05	0.04	0.02	0.27	2.53	11.37
Capital asset ratio	0.32	0.26	0.26	-1.53	1.00	-0.07	6.45
Return on equity	-0.09	0.04	1.79	-45.54	8.88	-19.96	500.15
Money supply (%)	28.48	24.70	10.74	7.20	80.80	1.56	7.33
GDP growth (%)	2.58	2.00	2.98	-7.00	18.00	0.67	7.08
Inflation (%)	7.79	6.80	15.69	-35.80	302.10	15.86	298.67
Reg. quality (index)	-0.50	-0.43	0.34	-2.21	0.68	-0.44	4.67
Ease of getting credit (Index)	33.08	18.75	17.62	12.50	87.50	0.75	2.61

Table A6: Correlation matrix

	1	2	3	4	5	6	7	8	9	10
(1) Loan growth (ratio)	1									
(2) Credit risk (ratio)	-0.256***	1								
(3) HHI (index)	-0.0203	0.129***	1							
(4) Capital asset ratio	0.0802*	-0.174***	0.0628	1						
(5) Return on equity	0.0463	-0.144***	-0.0428	0.0509	1					
(6) Money supply (%)	-0.0497	0.0443	0.234***	-0.0758*	-0.0313	1				
(7) GDP growth (%)	0.100**	-0.0733*	0.0412	0.0996**	0.0756*	-0.171***	1			
(8) Inflation (%)	-0.189***	0.119***	0.0991**	0.0673	-0.0334	0.0327	-0.126***	1		
(9) Regulatory quality (index)	0.0625	-0.105**	0.0672	-0.00912	-0.0245	0.374***	0.0916**	-0.236***	1	
(10) Ease of getting credit (index)	0.0116	0.0420	0.418***	0.0532	-0.0594	0.308***	0.145***	0.183***	0.363***	1

Table A7: Descriptive statistics

	Mean	S.D.	Min	Max	Skew	Kurt
Credit risk	0.12	0.15	0.00	2.08	4.99	45.24
Loan growth	0.29	0.52	-2.54	5.31	2.78	27.04
Loan growth sq.	0.35	1.54	0.00	28.23	12.87	206.14
Prov. for loan impairment	0.02	0.03	-0.15	0.36	3.54	29.48
Capital asset ratio	0.32	0.26	-1.53	1.00	-0.07	6.44
Return on equity	-0.09	1.80	-45.54	8.88	-19.91	497.24
Private credit	17.48	10.52	2.00	78.30	2.57	13.67
GDP per capita growth	2.59	2.99	-7.00	18.00	0.66	7.05
Inflation	7.79	15.73	-35.80	302.10	15.82	297.32
Political stability	-0.54	0.73	-2.37	1.18	-0.59	2.49
Ease of getting credit	33.11	17.64	12.50	87.50	0.75	2.60

Table A8: Correlation matrix

	1	2	3	4	5	6	7	8	9	10
1. Loan growth	1									
2. Loan growth squared	0.672^{***}	1								
3. Prov. for loan impairment	-0.0473	0.0147	1							
4. Capital asset ratio	0.0804^{**}	0.0277	0.0513	1						
5. Return on equity	-0.0129	-0.0212	-0.0263	-0.0227	1					
6. Private credit	-0.0144	-0.0328	0.0725^{*}	-0.0215	-0.0208	1				
7. GDP per capita growth	0.110^{***}	-0.00908	-0.00226	0.118^{***}	0.0316	-0.095^{**}	1			
8. Inflation	-0.163^{***}	0.101^{**}	0.0884^{**}	0.0671^{*}	-0.0213	-0.0773^{*}	-0.113^{***}	1		
9. Political stability	-0.0736^{*}	-0.0129	-0.0204	0.0530	0.0266	0.119^{***}	0.0746^{*}	-0.164^{***}	1	
10. Ease of getting credit	0.0407	0.00700	0.180^{***}	0.0912^{**}	-0.0538	0.486^{***}	0.123^{***}	0.176^{***}	-0.230^{***}	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: Credit risk determinants in SSA, alternative specifications

	The dependent variable is credit risk (in logs)		
	RE	FE	OLS
Credit risk (L1)	0.29***	0.11**	0.40***
	(0.054)	(0.043)	(0.033)
Loan growth	-0.89***	-0.89***	-0.83***
	(0.168)	(0.207)	(0.185)
Loan growth squared	0.46***	0.37**	0.45***
	(0.115)	(0.159)	(0.144)
Provision for loan impairment	0.18***	0.16***	0.19***
	(0.032)	(0.034)	(0.029)
Capital asset ratio	0.05	0.06	0.01
	(0.178)	(0.369)	(0.139)
Return on equity	-0.00	0.12*	-0.05
	(0.058)	(0.072)	(0.058)
Private credit	0.00	0.03***	0.00
	(0.004)	(0.010)	(0.003)
GDP per capita growth	-0.01	-0.00	-0.02*
	(0.010)	(0.015)	(0.010)
Inflation	-0.01*	-0.01	-0.01
	(0.006)	(0.008)	(0.006)
Political stability	-0.01	-0.01	-0.02*
	(0.009)	(0.011)	(0.010)
Ease of getting credit	0.56***	0.63***	0.51**
	(0.149)	(0.225)	(0.239)
Constant	-1.02***	-1.74***	-0.50*
	(0.244)	(0.383)	(0.280)
No of observations	394	394	394
R-squared	0.45	0.31	0.47
Wald chi2	218	4.21	13.43

The choice between random effects and fixed effects model is determined by the Hausman test. Results for this test yield a Chi2 (24)=67.94, prob=0.000. On this basis, the null hypothesis that random effects provide consistent estimates is strongly rejected.

Table A10: Summary statistics of the variables used in the regressions

	2015 (N=8665)					2013 (N=6449)				
	Mean	Std. Dev.	Median	Minimum	Maximum	Mean	Std. Dev.	Median	Minimum	Maximum
MFI loan	0.11	0.31	0.00	0.00	1.00	0.10	0.30	0.00	0.00	1.00
M-money	0.69	0.46	1.00	0.00	1.00	0.62	0.48	1.00	0.00	1.00
Income	16,092	181,685	6,000	0.00	15,150,000	7,228	17,526	3,000	0.00	450,000
Age	37.20	16.57	33.00	16.00	100.00	36.54	15.53	32.00	16.00	97.00
Male	0.39	0.49	0.00	0.00	1.00	0.41	0.49	0.00	0.00	1.00
Married	0.60	0.49	1.00	0.00	1.00	0.64	0.48	1.00	0.00	1.00
Educated	0.82	0.38	1.00	0.00	1.00	0.85	0.36	1.00	0.00	1.00
HH size	4.39	2.49	4.00	1.00	20.00	4.46	2.54	4.00	1.00	24.00
Rural	0.56	0.50	1.00	0.00	1.00	0.36	0.48	0.00	0.00	1.00
M-banking	0.19	0.39	0.00	0.00	1.00	-	-	-	-	-
M-credit	0.10	0.29	0.00	0.00	1.00	-	-	-	-	-
Poor	0.41	0.49	0.00	0.00	1.00	0.32	0.47	0.00	0.00	1.00

Table A11: Correlation matrix (2015, N=8665)

	1	2	3	4	5	6	7	8	9	10	11
1) MFI loan	1										
2) M-money	0.197***	1									
3) M-banking	0.154***	0.291***	1								
4) M-credit	0.145***	0.208***	0.670***	1							
5) Income	0.038***	0.036***	0.020	0.018	1						
6) Age	0.112***	-0.059***	-0.139***	-0.091***	0.017	1					
7) Male	0.048***	0.078***	0.121***	0.098***	0.031**	0.039***	1				
8) Married	0.104***	0.097***	0.003	0.005	0.027*	0.088***	-0.0141	1			
9) Education	0.135***	0.368***	0.213***	0.151***	0.022*	-0.312***	0.115***	-0.0179	1		
10) HH size	-0.035**	-0.136***	-0.106***	-0.075***	-0.025*	-0.114***	-0.0787***	0.195***	-0.109***	1	
11) Rural	-0.042***	-0.187***	-0.211***	-0.157***	-0.038***	0.149***	-0.0161	0.0657***	-0.191***	0.203***	1

Table A12: Correlation matrix (2013, N=6112)

	1	2	3	4	5	6	7	8
1) M-money	1							
2) Income	0.159***	1						
3) Age	-0.067***	-0.009	1					
4) Male	0.038**	0.100***	0.087***	1				
5) Married	0.115***	0.076***	0.031*	0.026*	1			
6) Education	0.344***	0.108***	-0.283***	0.056***	0.054***	1		
7) HH size	-0.058***	-0.025*	-0.041**	-0.079***	0.202***	0.017	1	
8) Rural	0.175***	0.150***	-0.131***	-0.003	-0.077***	0.166***	-0.212***	1

Table A13: IV 2SLS estimates of the probability of using MFI credit by poverty status (2016)

	Dependent variable: Dummy = 1 if ever used MFI loan, 0 otherwise					
	(a)	(b)	(c)	(d)	(e)	(f)
	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
M-money	-0.02	-0.10***				
	(0.022)	(0.027)				
M-banking			0.04	-0.07***		
			(0.031)	(0.024)		
M-Credit					0.07	-0.05**
					(0.049)	(0.026)
Income	0.18***	0.26***	0.16***	0.26***	0.16***	0.26***
	(0.051)	(0.033)	(0.043)	(0.034)	(0.042)	(0.033)
Age	-1.25**	-2.32***	-1.19**	-2.62***	-1.21***	-2.63***
	(0.490)	(0.481)	(0.474)	(0.538)	(0.468)	(0.538)
Age squared	0.18***	0.34***	0.17***	0.38***	0.18***	0.38***
	(0.068)	(0.066)	(0.066)	(0.073)	(0.065)	(0.074)
Male	-0.08***	-0.10***	-0.07***	-0.09***	-0.08***	-0.10***
	(0.021)	(0.021)	(0.019)	(0.020)	(0.019)	(0.020)
Married	-0.05***	-0.03*	-0.04***	-0.03*	-0.05***	-0.03*
	(0.017)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)
Education	0.01	0.07***	0.01	0.05*	0.01	0.05*
	(0.016)	(0.026)	(0.016)	(0.027)	(0.016)	(0.027)
HH Size	0.02**	0.05***	0.02**	0.05***	0.02**	0.05***
	(0.009)	(0.011)	(0.008)	(0.011)	(0.009)	(0.011)
Rural	0.02	0.05***	0.02	0.05***	0.02	0.05***
	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)	(0.015)
No of obs.	3,473	5,056	3,473	5,056	3,473	5,056
Wald Chi2	123.4	527.6	129.6	533.0	128.1	541.2
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Exogeneity test	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is usage of microcredit dummy. IV refers to instrumental variable. Robust standard errors are reported (in parentheses). ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. All regressions include a constant county dummies but these are not reported. Exogeneity test for IV 2SLS is the Durbin-Wu-Hausman test as described in Cameron and Trivedi (2010). The p-values for the DWH test are reported.